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An investigation into the causes and characteristics of fraud in Kenyan SACCOs and whether Benford's Law can be used to detect fraud in the accounting data

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An Investigation into the Causes and Characteristics of Fraud in Kenyan SACCOs and Whether Benford's Law can be used to Detect Fraud in the Accounting Data

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Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Abstract

Financial statement fraud is a significant threat facing the survival of the co-operative movement in Kenya. The threat has led to a number of amendments to the Co-operative Societies Act of 1997. The Sacco Societies Regulatory Authority (SASRA) is a Semi-Autonomous Government Agency inaugurated in 2009 charged with the prime responsibility to licence and supervise deposit taking Sacco Societies in Kenya. However, fraud continues to appear in the media despite inspections of co-operative societies sanctioned and carried out by the regulator. Owing to numerous cases of fraud that occur in SACCOs, there is a need for measures to detect fraud in order to ensure the sustainability of this sector of the economy. The financial ratios currently computed by SACCOs in Kenya might not assist users of the financial reports to detect fraudulent financial reports. Extra efforts are therefore needed to unearth fraud in SACCOs. This study seeks to investigate the applicability of Benford's Law to detect fraud in accounting data. Benford`s Law is a statistical tool used to test evidence of human bias and data manipulation. The study attempts to help auditors in their investigation of fraudulent activities in this crucial sector. Two sets of secondary data were used to test whether Benford's Law could be used to detect fraud in SACCOs. The first set consisted of data from SACCOs with fraud while the second set consisted of SACCOs without fraud. Percentages were used to analyze the first digit of all the line items of the balance sheet, the statement of changes in equity, the income statements, the appropriation account, the cash flow statement, disclosures and notes in the financial statements per SACCO was binned into nine bins of 1 to 9. Chi-Square test statistic was also used to determine the goodness of fit between Benford's Law and the SACCO transactional level data at 5% confidence level.The first digit entries for SACCOs with fraud partially followed Benford's Law for both SACCOs with and without fraud. Benford's Law can therefore be used detect fraud in fraudulent financial statements in Kenyan SACCOs.

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Dedication

I dedicate this research thesis to my parents Mr and Mrs Kamau.

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CHAPTER ONE

INTRODUCTION

1.1 Background

1.1.1 Fraud

Fraud is a deception deliberately practiced in order to secure unfair or unlawful gain. Fraud comes in many shapes and sizes. It goes by several different names, including internal fraud, occupational fraud, or employee dishonesty. There are three basic types of fraud namely asset misappropriation, bribery and corruption, and financial statement fraud. Many fraud schemes are perpetrated by employees (Coenen, 2014).

According to Coenen (2014) asset misappropriation is the most frequent type of fraud, probably because it is the easiest scheme to understand.Asset misappropriation might include cheque forgery, theft of money, inventory theft, payroll fraud, or theft of services. Recent statistics show that asset misappropriation happens in over 91% of fraud schemes. This easily makes it the most common fraud, but statistics show that it is the least expensive fraud on a per-fraud basis. The next most frequently occurring fraud scheme is bribery and corruption, which is part of about 30% of all fraud that is uncovered. Bribery and corruption include schemes such as kickbacks, shell company schemes, bribes to influence decision-making, manipulation of contracts, or substitution of inferior goods. The average bribery/corruption scheme is far more costly than asset misappropriation.

The least common type of fraud is financial statement fraud. Although it occurs least frequently, in only 10% of all fraud cases, it is easily the most expensive in terms of value lost. This type of fraud centers on the manipulation of financial statements in order to create financial opportunities for an individual or entity. Fraudulent financial statements involves manipulation of stock price, increased year-end bonuses, favorable loan terms, or other indirect benefits from the financial statement fraud (Coenen, 2014). Corporate fraud may be as a result of a combination of asset misappropriation, bribery and corruption, and financial statement fraud that can be difficult to prevent and to catch. By creating effective policies, a system of checks and balances and physical security, a company may limit the extent to which fraud can take place. It is considered a white collar crime (Investopedia, 2014).

Corporate scandals such as Enron, Tyco, WorldCom and Adelphia have drawn significant attention to the occurrence of fraud. The Association of Certified Fraud Examiners ("ACFE") estimated the amount of fraud-related losses reached US$650 billion in 2006 (Wells, 2008). The prevalence and consequences of fraud affect the shareholders, creditors, auditors and the public's confidence in the financial system, including the integrity of the financial statement (Rezaee, 2005).

Fraud detection is becoming increasingly important to managers of organizations, to internal and external auditors, and to regulators. Revelations of fraud-related problems at HealthSouth, Enron, and WorldCom, and the Sarbanes-Oxley Act stress the importance of early detection of fraud (Reinstein, Moehrle and Reynolds-Moehrle, 2006). Financial statement frauds have weakened investor confidence in corporate financial statements, led to a decrease in market capitalization, and have contributed to four of the ten largest bankruptcies in history (Albrecht, 2003). The following relatively higher profile cases from various eras and cultures illustrate the decisions that fraud perpetrators and others complicit in frauds often make, which otherwise are reflective of other observed fraud cases. Clear themes emerge when studying them in tandem.

1.1.2 SACCOs in Kenya

This study focuses on SACCOs in Kenya. SACCO is an acronym of Savings and Credit Cooperatives. SACCOs are defined as democratic, unique, member driven, self-help, not for profit financial co-operatives (Afya SACCO, 2005). They are owned and governed by members with the same common bond. SACCOs in Kenya or the SACCO movement in Kenya is billed as the largest in Africa and among the top 10 globally. With over Ksh 230 billion in assets and a savings portfolio estimated at Ksh 190 billion, the SACCO movement in Kenya constitutes a significant proportion, about 20 per cent, of the country's domestic savings (Ministry of Co-operative Development and Marketing, 2012).

The co-operative movement in Kenya may be traced to the pre-independence times with accelerated development in the period immediately after the country attained independence (Wanyama, 2009). The movement has played an important role in wealth creation, food security and employment generation and, hence, contributed significantly to poverty alleviation. To date, there are over 5,000 registered co-operative societies country-wide. The

membership is over 8 million and has mobilized domestic savings estimated at over $2.5 billion. The co-operatives have employed over 300,000 people besides providing opportunities for self-employment to many more. The co-operatives in Kenya are organized into service and producer entities and cut across various sectors. The co-operatives have made remarkable progress in agriculture, banking, credit, agro-processing, storage, marketing, dairy, fishing, housing and transport. Service co-operatives are the closest to communities, are organized on a shareholder basis and are formed by individual members of organizations voluntarily working in a specific geographic area (Wanyama, 2009).

SACCOs have become a vital component of Kenya's economic and social development. With the sector controlling such huge resources and the savings, there have been numerous cases of theft and misappropriation of funds which necessitated the Kenyan Government to come up with the legislation to regulate the sector. The Sacco Societies Regulatory Authority (SASRA) is a Semi-Autonomous Government Agency under the Ministry of Cooperative, Development and Marketing. It is a creation of the Sacco Societies Act 2008 and was inaugurated in 2009 charged with the prime responsibility to licence and supervise deposit taking Sacco Societies in Kenya. The Authority derives its powers to regulate the deposit taking Sacco Societies in Kenya from the Sacco Societies Act 2008 and the Regulations issued there under (Ministry of Co-operative Development and Marketing, 2012).

Mugwe (2012) cited the case of a mega fraud in Harambee SACCO that involved members paying loans and cashiers made entries into the computers, but for some reason the money was not banked. One cashier could not explain the whereabouts of Sh324 million while another could not account for Sh30 million. The amounts were way above the limits cashiers are allowed to hold. In another scheme, directors, employees and members got huge cash payments as loans and had the transactions deleted from the SACCO's system, leaving them with no debt obligations. Members and outsiders further used automated teller machines to rob the SACCO of more than Sh100 million.

1.1.3 Benford's Law

In 1881, Astronomer and Mathematician Simon Newcomb published an article in the American Journal of Mathematics unfolding his observation that books of logarithms in the library were soiled and worn out because they were more used in the beginning and less used

towards the end of the log table. From this he concluded that researchers using the logarithm tables were looking up numbers starting with 1 more often than numbers starting with 2, those with 2 more often than 3, and so on as first digits in numbers.

Newcomb's article did not get much popularity, and 57 years later General Electric physicist Frank Benford, apparently not informed of Newcomb's article, made exactly the same observation about logarithm tables and also made a conclusion of the same logarithm law. Benford concluded that it was doubtful that physicists and engineers had some special fondness for logarithms starting with 1. He performed a mathematical analysis of 20,229 sets of numbers, including very dissimilar categories such as the areas of baseball statistics, rivers, numbers in magazine articles and the street addresses of the first 342 people listed in the book "American Men of Science." All these apparently unrelated sets of numbers followed the same first-digit probability pattern as the soiled pages of logarithm tables suggested. In all these mathematical tests, the number 1 turned up as the first digit about 30 percent of the time, more often than any other. Benford's Law predicts a decreasing frequency of first digits, from 1 all through to 9.

Benford derived a formula to explain this phenomenon. If absolute certainty is defined as 1 and absolute impossibility as 0, then the probability of any number "d" from 1 through 9 being the first digit is log to the base 10 of (1 + 1/d).
This formula gives posterior frequencies of numbers found in many categories of statistics.

$P(d = m) = \log_{10}((m + 1)/ m)$, for m = 1, 2, 3, …,9.

This probability distribution gives

$P(d = 1) = \log 2 = .301$

$P(d = 2) = \log(3/2) = .176$

on up to $P(d = 9) = \log(10/9) = .046$.

	Position in Number			
Digit	1st	2nd	3rd	4rd
0		0.11968	0.10178	0.10018
1	0.30103	0.11389	0.10138	0.10014
2	0.17609	0.10882	0.10097	0.10010
3	0.12494	0.10433	0.10057	0.10006
4	0.09691	0.10331	0.10018	0.10002
5	0.07918	0.09668	0.09979	0.09998
6	0.06695	0.09337	0.09940	0.09994
7	0.05799	0.09035	0.09902	0.09990
8	0.05115	0.08757	0.09864	0.09986
9	0.04576	0.08500	0.09827	0.09982

Figure 1.1: First to fourth digit according to Benford's Law

Source: Nigrini (1996)

1.1.4 A Simple Application of Benford's Law

Benford's Law can be found in inflationary price increases. The price of an item that starts out at a cost of Kes 1.00 with a steady 3% rate of annual inflation will have a leading digit of 1 for 24 years (1st year =1.03, 2nd year = 1.0609 and so on until the price reaches Kes 2.03 in the 25th year. The leading digit will be 2 for the next 14 years, 3 for the following 9 years, 4 for 8 years, 5 for 6 years...and 9 for only 3 years before the price reaches Kes10.03 in the 79th year. After that, the leading digit will be a 1 again for another 24 years.24 years divided by 79 years you get 30.3%.

The increase from 1 to 2 million represents an increase of 100%. Conversely, the increase from 2 million to 3 million is 50%, 3 to 4 is 33%, …. and 9 to 10 is 11.1%. Hence, if wealth grows exponentially by compound interest, the first million is indeed the hardest, because imagine starting from 100,000 then 1,000,000 means increasing it by a factor 10 whereas the second million is only an increase by a factor 2.

1.1.5 Case Scenario on application of Benford`s Law in fraud detection

A bank's policy is to refer loans at or above Kes 50,000 to a loan committee. A loan officer's potential to perpetrate fraud will just be below the approval threshold. If loan fraud was being perpetrated, a Benford's Law test of looking at either the leading digit (specifically, the four) or two leading digits (specifically, 49) has the potential to uncover the fraud. Figure 2 shows what a Benford's Law test of the leading digit might show as a result in this particular scenario. The line is Benford's Law probabilities and the bars are the actual occurrences. Note that 4 is abnormally high in occurrence, and 5 is too low, indicating the possible manipulation of the natural occurrence of loans beginning with 5 (Kes 50,000 loans) possibly being switched to just under the cutoff or indicating that the suspect could be issuing a lot of Kes 49,999.99 loans fictitiously to embezzle funds.

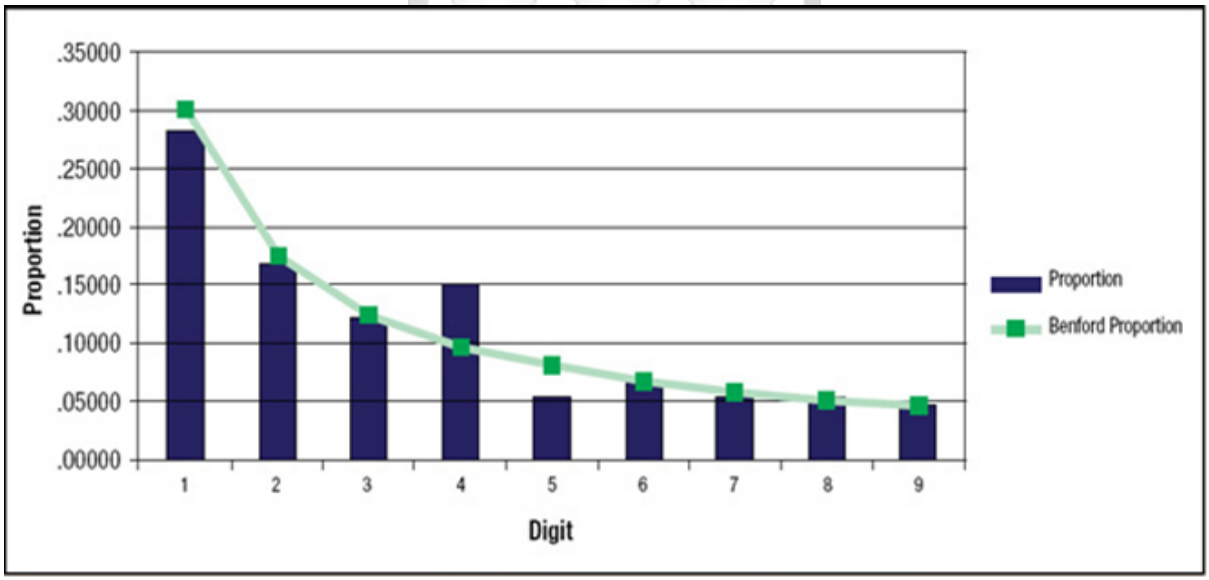


Figure 1. 1: Benford's Law Test/Comparison

Source: Tommie (2011)

This is contrary to what one may think that number 1 would appear as the first digit 11% of the time (1/9) as a uniform distribution. These empirical studies led Benford to propose that in many real world applications the first digits *d* follow the probability distribution. The probabilities are based on mathematical logarithms of the occurrence of digits in randomly generated numbers in large data sets. Benfords Law is used to test evidence of human bias.

1.2 Problem Statement

According to the Ministry of Co-operative Development and Marketing (2008), Financial statement fraud is the most significant challenge facing the co-operative movement in Kenya. Many cases of fraud were investigated in the co-operative sector in Kenya where 37 investigations were carried out in 2007 financial year alone (MOCDM, 2008). This has led to a number of amendments to the Co-operative Societies Act of 1997. However, fraud continues to appear in the media despite inspections of co-operative societies sanctioned and carried out by the regulator (Lari, 2009).

There is much empirical evidence suggesting that the frequencies of first and second digits of a data set that contains credible numbers will indeed correspond to a Benford's Law probability distribution (Nigrini 1996). Given its potential to identify data points (e.g., transaction amounts) that contain characteristics associated with fraudulent activity, using Benford's Law holds great promise as a fraud detection process (Coderre, 1999).

Owing to numerous cases of fraud that have faced the SACCOs, Lari (2009) saw a need for measures to detect fraud in order to ensure sustainability of this subsector. The financial ratios currently computed by SACCOs in Kenya might not assist users of the financial reports towards detection of fraudulent financial reports (Lari, 2009). Extra efforts are therefore needed to unearth fraud in the SACCOs. This study sought to identify the factors causing fraud in Kenyan SACCOs, characteristics of fraud and establishing application of Benford's Law in fraud detection. This is in an attempt to help auditors in their investigation of fraudulent activities in this crucial sector.

1.3 1.3 Research Objectives

1.3.1 Main Objectives

The purpose of this study is to investigate whether Benford's Law can be used by auditors in detecting fraud in Kenyan SACCOs accounting data

1.3.2 Specific Objectives

1. To assess the factors causing fraud in Kenyan SACCOs.
2. To analyse the characteristics of fraud in Kenyan SACCOs.
3. To examine fraud detection technique/approaches used in Kenyan SACCOs.

4. To investigate the applicability of using Benford's Law for fraud detection in Kenyan SACCOs data by auditors.

1.4 1.4 Research Questions

1. What are the factors causing fraud in Kenyan SACCOs?
2. What are the characteristics of fraud in Kenyan SACCOs?
3. What are the fraud detection techniques/approaches used in Kenyan SACCOs?
4. How can Benford's Law be used by auditors for fraud detection in Kenyan SACCOs?

1.5 1.5 Justification of the Study

The findings of this study will be valuable in many ways. Firstly, it will add knowledge towards improving the detection and prevention of fraud as the characteristics and causes of fraud will be analyzed. Due to technological advancement, the use of data mining will continue to benefit the accounting profession. This thesis finds out whether data mining by use of Benford's Law is useful in all areas of accounting, such as auditing, fraud detection, and improper payments for early fraud detection and hence increases investor confidence. Financial managers, auditors, and fraud examiners are interested into finding out automated, timely approach to finding out financial frauds. Investors and portfolio managers all want a dependable and reliable, automated process to help them filter through large quantity of financial data to find the firms that give investors inaccurate information.

It will also expand the existing literature concerning fraud in financial reporting as well as aid government in monitoring of SACCOs. The findings will provide new insights for policy makers, regulators, and scholars.

1.6 1.6 Scope

This study focused on factors causing fraud in SACCOs, characteristics of fraud and SACCOs accounting data to assess whether the data follow Benford's Law for both SACCOs where fraud has been detected and those without fraud in Kenya. Primary and secondary data was obtained from the SACCOs and the regulator respectively. The data obtained from Kenya Gazette was for 2009 to 2011 financial year because it is current hence useful in making conclusions.

1.7 1.7 Limitations

Failure for data to follow Benford's Law may not necessarily indicate fraud but an error could have occurred or a pre-authorized transaction. However, non conformance to the law may lead the forensic auditor to identify an error. Secondly, there could be other methods of fraud detection that could be combined with Benford's Law such as ratios but are not used in this particular study. In addition, there could be incomplete reporting in the data provided and this may influence the outcome of the study. Access to the data is also expected to be a challenge since SACCOs are not under obligation to disclose their financial statements publicly. Through the regulator however, and by following the right channels, the data was accessed for use in the study.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter covers review of relevant literature regarding fraud. It starts with a review of theories that are related to the study, followed by the factors causing fraud and move on to review elements of fraud. The history, concept and the application of Benford's Law in fraud detection is also reviewed. The chapter ends with a review of theories that are related to the study with the factors causing fraud and move on to review elements of fraud.

2.2 Theoretical Framework

This study looked at theories that are related to fraud in organizations. These theories include corporate governance theories and occupational fraud theories which were used as a basis of research under SACCOs financial statement misrepresentation or fraudulent financial reporting. Financial statement fraud was also examined to give a background to impetus of fraudulent activities in organizations. Failure in corporate governance is a source of various financial misrepresentations.

2.2.1 COPORATE GOVERNANCE THEORIES

2.2.1.1 Agency Theory

Agency theory relative to corporate governance assumes a two-tier form of firm control. Albrecht et al (2004) describes agency theory as a principal-agent relationship between shareholders and management, with top managers acting as agents whose personal interests do not naturally align with company and shareholder interest. This line of reasoning comes from economic models that argue that all people are only motivated by self-interest and self-preservation. The theory holds that a person is a rational actor when he or she seeks to maximize his or her own utility in each situation. Given the two options, the rational person will prefer the option that most increases his or her own individual utility. It explains their differences in behaviour or decisions by noting that the two parties often have different goals and, independent of their respective goals, may have different attitudes toward risk.

The design of mechanisms for effective corporate control to make managers act in the best interest of shareholders has been a major concern in the area of corporate governance and finance (Allen and Gale, 2001), and continuing research in agency theory attempts to design an appropriate framework for such control. In a corporation, the shareholders are the principals and the managers are the agents working on behalf of, and for the interests of, the principals. In agency theory, a well-developed market for corporate controls is assumed to be non-existent, thus leading to market failures, non-existence of markets, moral hazards, asymmetric information, incomplete contracts and adverse selection among others. Various governance mechanisms have been advocated which include monitoring by financial institutions, prudent market competition, executive compensation, debt, developing an effective board of directors, markets for corporate control, and concentrated holdings. These mechanisms are in crude stages as far as SACCOs are concerned and therefore corporate governance values are not there to check against fraud.

2.2.1.2 Stewardship Theory

This theory, as an alternative to agency theory, has been highlighted to have a more wholesome and realistic lens from which to view management actions and motivations (Albrecht et al, 2004). Whereas agency theory is based on economic models, stewardship theory is based on psychological and sociological aspects. According to Sundaramurthy and Lewis (2003), the theory holds managers as stewards who will advocate for the best interests of the shareholders as opposed to their self interests regardless of personal motivations or incentives. For stewardship theory, managers seek other ends besides financial ones. These include a sense of worth, a good reputation, a job well done, a feeling of satisfaction and a sense of purpose. The stewardship theory holds that managers inherently seek to do a good job, maximize company profits and bring good returns to stockholders. They do not necessarily do this for their own financial interest, but because they feel a strong duty to the firm (Sundaram and Inkpen, 2004).

The executive manager, under this theory, far from being an opportunist, essentially wants to do a good job, to be a good steward of the corporate assets. Thus, stewardship theory holds that there is no inherent, general problem of executive motivation. Given the absence of an inner motivational problem among executives, there is the question of how far executives can achieve the good corporate performance to which they aspire. Thus, stewardship theory holds

that performance variations arise from whether the structural situation in which the executive is located facilitates effective action by the executive. The issue becomes whether or not the organization structure helps the executive to formulate and implement plans for high corporate performance (Davis, Schoorman, and Donaldson, 1997).

2.2.2 Occupational Fraud Theories

According to ACFE (2012), occupational fraud schemes involve an employee abuse of trust placed in him or her by an employer for personal gain. The formal definition of occupational fraud is the use of one's occupation for personal enrichment through the deliberate misuse or misapplication of the employing organization's resources or assets. The Association further classifies occupational fraud into three categories. Corruption includes conflict of interest (purchasing and sales schemes), bribery (invoice kickbacks and bid rigging), illegal gratitude and economic extortion. Asset misappropriation entails loss of cash (theft of cash on hand or cash receipts) and misuse of inventory and other assets for personal enrichment. Financial statement fraud involves asset or revenue overstatement (Timing differences, fictitious revenues, concealed expenses and liabilities, improper asset valuation and improper disclosures) as well as asset or revenue understatements (Timing differences, understated revenues, overstated expenses and liabilities, improper asset valuation).

Wells (2008), defined white-collar crime as violations of law which involve the use of a violator's position of economic power, influence, or trust in the legitimate economic or political institutional order for the purpose of illegal gain, or to commit an illegal act for personal or organizational gain.ACFE (2016),defined differential association theory as criminal behaviour learnt through interaction with other persons in a process of communication. It is acquired through participation within intimate social groups and involves all the mechanisms that are required in any other learning. Learning differs from pure imitation. Criminal behaviour is not explained just through needs and values.

Occupational fraud such as asset misappropriations, corruption, and fraudulent financial reporting, is a widespread problem that affects practically every organization, regardless of size, location, or industry. In contrast, ACFE (2012) indicates that early studies (Hollinger and Clark 1983; Sutherland 1983; Albrecht, Wernz et al. 1995) focused primarily on

developing a model of the occupational offender. Cressey's study (1973) articulated the three factor model for fraud: 1) a perceived unsharable financial need – such as personal failures, business reversals, physical isolation, or status gaining – 2) a perceived opportunity - when information about a member's deeds may be unknown to others or when misbehaviours are not easily detected- and 3) rationalization. Similarly, Albrecht, Wernz et al. (1995) suggest that three factors are involved in occupational fraud: personal, situational, and some way to rationalize the act.

In the context of traditional organizations, Cressey (1973) and Hollinger and Clark (1983) propose that employee fraud is mainly a result of workplace conditions: employee theft is significantly related to job dissatisfaction. Research on occupational fraud suggests that the level of employee dissatisfaction relates to dysfunctional behavior. These studies disclose several pertinent relationships between the perpetrators and the frauds they committed: lack of segregation of responsibilities, placing undeserved trust in key employees, imposing unrealistic goals, and operating on a crisis basis were all pressures or weaknesses associated with fraud.

Sutherland (1983) believes that learning of criminal behavior occurs with other people in a process of communication. A learning process involving two specific areas: the techniques to commit the crime, and the attitudes, drives, rationalizations, and motives of the criminal mind. Conner (2003) explored the existence of this relationship between referent selection and the changing nature of organizations; this relationship potentially undermines how members of SACCOs form judgments and make decisions, and how performance measures and incentives affect motivation and performance.

Hollinger and Clark (1983) also suggest that every employee can be tempted to steal from his employer - motivations and opportunities seem to be interactive: the greater the economic need, the less weakness in internal controls is needed to accomplish the fraud; the greater the weakness in controls, the less motivational need (Bologna and Lindquist, 1995). The theory assumes that people are greedy and dishonest by nature. Ample anecdotal and empirical evidence also indicates that this human factor is the weakest link in occupational fraud (Hecht and Murphy, 2000).

In the cooperatives sector, a prior study Lewis(1937) concluded that difficulties that lead to SACCOs failure: faults due to poor management by non-compliance of key cooperatives principles and faults due to lack of team sprit amongst staff and members.

Paradis (2001)concludes that failure of SACCOs are indirectly determined by poor governance. He goes ahead to conclude that with multiple ownership and no secondary market of equities exist(as the case is in Kenya) the conflict between management and members cause failures in SACCOs.

2.3 Benford's Law

Benford's Law is also called the first-digit law. It states that in lists of numbers from many real-life sources of data, the leading digit is distributed in a specific, non-uniform way. According to this law, the first digit is 1 about 30% of the time, and larger digits occur as the leading digit with lower and lower frequency, to the point where 9 as a first digit occurs less than 5% of the time.

2.3.1 Authors in agreement on Application of Benford's Law in Fraud Detection

In auditing, Benford's Law has been shown to be widely applicable in a number of auditing contexts, including external, internal, and governmental auditing contexts. For example, Nigrini and Mittermaier (1997) show how auditors can use Benford's Law as an analytical procedure to help discover surprising patterns in transaction activity. It is likely that an individual making fraudulent accounting entries will enter the same amount (or similar amounts) many times. In that type of situation, the resulting variation of first and second digits from the Benford Law probability distribution may lead the auditor to discover the fraudulent transactions.

Nigrini (1999a) was the first to highlight the potential of Benford's Law as an effective fraud detection process. He outlined a number of practical applications where a fraud auditor could effectively employ digital analysis using Benford's Law including accounts payable data, general ledger estimations, duplicate payments, tax returns and customer refunds. Nigrini (1999a) also highlighted the role of the computer in completing a Benford's Law analysis. Tapp and Burg (2001) also describe the role of technology advances in fraud detection processes. In so doing, they describe the use of Benford's Law in three different fraud

contexts; detecting vendor kickbacks, detecting fictitious vendors, and detecting overstated divisional performance.

Importantly, Benford's Law has also been shown to be an effective tool for internal and governmental auditors as well. Nigrini (1999b) outlines a number of different contexts where a digital analysis can add value for internal auditors, including the revenue, canceled checks, inventory, and disbursement areas. Nigrini (1996) also demonstrated the applicability of Benford's Law in a taxpayer compliance context, raising the possibility of its effectiveness as a tool for Internal Revenue Services (IRS) auditors. Finally, Wallace (2002) describes the usefulness of Benford's Law in a governmental context. Given its apparent wide applicability, it is not surprising that the IRS and the Institute of Internal Auditors are working on better and different ways to use Benford's Law (Maney, 2000).

According to Tackett et al (2006) U.S Congress approved the Sarbanes-Oxley Act of 2002 (SOX) which requires organizations to report on the operating effectiveness of their internal controls over financial reporting. Furthermore, the independent auditor is required to evaluate and report on the effectiveness of their client's internal controls, and they must confirm to management's internal control assessment. Notable omission from SOX is a requirement that independent auditors must employ fraud specialists in their independent audits of SEC filers. Qualitative analysis reveals that utilizing fraud specialists on independent audits has positive net advantages to financial reporting. Recommendations are made regarding the types of fraud detection/deterrence skills and techniques like Benford's Law would be advantageous to independent auditors. SEC filers are typically large and complex business entities that are rife with opportunities for occupational fraud. Even with the internal control reporting requirements of Sarbanes-Oxley, significant opportunities for financial statement fraud exists because of management collusion.

According to Savile (2006), Benford's Law is astonishing the manipulators of information, such as accounting data, normally fail to observe the law. Savile (2006) utilized data taken from companies listed on the Johannesburg Securities Exchange to test the hypothesis that Benford's Law can be used to spot false or fraudulent reporting of accounting data. To examine the case, Benford's Law was applied to data generated by a set of 34 companies listed on the Johannesburg Securities Exchange. The test sample consists of data drawn from an equal number of so-called 'errant' and 'compliant' companies. Saville (2006) observed

that Benford's Law has the potential to act as a highly effective detector of data error or fraud in accounting information. The findings of the research is of great relevance to auditors, shareholders, financial analysts, investment managers, private investors and other users of publicly reported accounting data

According to Bhattacharya (2002), professional accountant's challenging and difficult task is to find out possible flaws in accounting control systems which may be used to misappropriate corporate funds; and correct or modify in good time. Nonetheless, despite tight controls fraudulent misappropriations and embezzlements do occur. A possible combination of a few interesting methods that include Benford's Law can be used to help and aid investigative and forensic accountants in tracking and tracing corporate frauds.

According to the ACFE (2012), there is obviously great benefit in detecting fraud schemes as close to their inception as possible, including the ability to limit the financial and reputational damage caused by the crime. Analyzing the duration of the occupational frauds reported, the ACFE report noted that the duration can provide insight into areas of opportunity for organizations to increase their fraud detection effectiveness. The median duration-the amount of time from when the fraud first occurred to when it was discovered-for all cases in our study was 18 months. This study highlights the usefulness of Benford's Law in fraud detection which can be employed in good time to arrest fraud, make the organizations recover their losses and save their reputation. According to Busta and Wienberg (1998), statistical approach of finding fraudulent data is to compare the frequency of digits in reported data to the Benford distribution of the expected frequency of the digits in numbers naturally issued from some fundamental process such as financial record-keeping. Deliberately altered numbers unusually conform to the Benford statistic so a deviation may signify the need for further examination.

According Dubinsky and Bruce (2001), fraud examiners, forensic accountants, and internal auditors are employing new investigative methods that depend on Benford's Law to spot acts such as bogus vendor payments, expense account fraud, and check-kiting schemes. In fact, many Fortune 500 U.S. companies use fraud detection methods based on Benford's Law. In the vast movement against white collar crime and corporate fraud, it is a very important tool for forensic accountants. According to Hill (1998), Frank Benford introduced the significant-digit logarithmic law which emphasizes that certain digits in numbers collected randomly can

occur often more than other numbers. Such logarithmic phenomenon has been identified and accepted by many mathematicians. Benford's Law can be applied in identifying accounting fraud and fabrication of data in financial documents.

According to Krakar and Zgela (2009), information systems auditing activities are necessary in today's business environment. There are numerous useful methods that can be performed in such audits one of methods is application of Benford's Law. Krakar and Zgela (2009) observed ways of application of Benford's Law in investigation of certain number set with aim to make a conclusion if number set conforms to Benford's Law.

According to Lee and Judge (2008) Clinical data is extremely important and necessary basis for medical decisions that reduce health risks. In addition to the usual noise and errors in experimental data, researchers have been known to massage the data to achieve a particular result or to reach a certain statistical significance level. In this context, a recent article in the New York Times Magazine discusses a well-known case of the intentional falsification of data from clinical experiments (Interlandi, 2006). Given the importance of clinical data integrity and the possibility of this type of fraudulent behavior, Benford's Law can be used to objectively identify and discover the presence of experimenter misrepresentations in the outcome of clinical research data. A set of clinical data that contains both correct and falsified clinical information is analyzed. Although, Scientific fraud is a rare phenomenon, using Benford's Law appears to be a quick and objective way to check authenticity of clinical data coming from researchers.

According to Lolbert and Tamas (2006), Benford's Law not only has theoretical aspects but it can be applied in detecting fraud and deliberate fabrication of data, in several fields, but most notably in auditing of financial statements. Lolbert and Tamas (2006) study gave an overview on Benford's Law and its history, lists the main mathematical results and initiates the most important application, digital analysis.

According to Lu et al (2006), adaptive Benford's Law is a digital analysis technique that identifies the probabilistic distribution of digits for many commonly occurring phenomena, even for incomplete data records. When tested to records of naturally occurring phenomena, adaptive fraud detection method uses variations from the expected Benford's Law

distributions as an indicators of irregular behavior that are strong indicators of fraud. Adaptive Fraud Detection method effectively identified actual fraudsters among the test data.

Nigrini and Mittermaier (1997) in their study initiated and described digital and number tests that auditors can be used as analytical procedures in the planning stages of the audit process. Several tests were presented that observed data for conformity of the digital frequencies to Benford's Law. Auditors could test the reliability and authenticity of lists by comparing the actual and expected digital frequencies. The results could help auditors in determining the nature and extent of other audit procedures.

According to Nigrinni and Mark (1999), Benford's Law provides a data analysis method that can help and aid CPAs towards possible errors, potential fraud, manipulative biases, costly processing inefficiencies and other irregularities. Nigrini and Miller (2009) further argued that Auditors are required to use analytical procedures to recognize the existence of unusual and odd transactions, events, and trends. Benford's Law gives the expected patterns of the digits in numerical data, and has been supported as a test for the validity and reliability of transaction level accounting data.

Wang and Yang (2009) noted that Auditors use computer aided audit software (CAATs) to make the process more accurate and reliable. As technology continues to progress, the use of data mining will continue to benefit the accounting profession. Wang and Yang (2009) pointed out that data mining by use of Benfords Law is useful in all areas of accounting, such as auditing, fraud detection, and improper payments. Data mining organizes data in such a way that it makes the accounting task easier. Scott (2005) showed in his research that a digital analysis method called Benford's Law can be applied to first-party automobile insurance claim data to detect number irregularities, which can be used in uncovering fraudulent automobile claim activity. Scott (2005) argued that with further research and development, Benford's Law has the potential to become a broadly used tool to discover insurance claim fraud.

The above findings involve various companies and institutions where Benford`s Law can be used by auditors to detect fraud other than SACCOs specifically from Kenya, hence setting a basis to this research.

2.3.2 Authors in disagreement on Application of Benford's Law in Fraud Detection

Use of Benford's Law has been criticized on a couple of grounds. First, since it is not universal, it cannot be used indiscriminately. The mathematical foundations of Benford's Law were first explicated in Hill (1995a,b), where it was established that Benford's Law was best satisfied if data from a random collection of data sets were amalgamated (and indeed, the best fit for Benford's twenty data sets occurs for their union). For valid inferences from its use on a single data set, its use must be justified. There have been studies concerning what probabilistic properties of data sets should cause them to satisfy Benford's Law.

A second criticism concerns the statistical procedure used to test with Benford's Law. Usual practice to investigate the first digit, for example, is to bin the data into nine bins, and use some kind of frequency comparison test, such as chi-squared, on the counts. Morrow (2010) and others have noticed that this test is conservative, sometimes extremely so, especially for large data sets. Gob (2007) did a thorough analysis of the use of chi-squared tests, particularly on very large data sets and identified the current inadequacy of formulating and testing the hypothesis of exact validity of Benford's Law.

Other types of fraud exist that cannot be detected by digital analysis because the data sets under examination are not appropriate for such analysis. For example, duplicate addresses or bank accounts cannot be uncovered, yet two employees with similar addresses might signal a shell company. Digital analysis will not detect such frauds as contract rigging, defective deliveries, or defective shipments.

Taylor (2010) indicated one possible shortcoming of Benford's Law is that, fraudsters can avoid detection by adhering to it. The distribution of first digits can be found on Wikipedia and other online sources. Another weakness is that the law works best on large data sets with lots of fudged numbers, but many frauds are based on just one or two. Benford is also generally only useful at the transactions level, not the portfolio level.

According to Durtschi et al (2004), Benford's Law offers the auditor with a tool that is simple and very effective for the discovery of fraud. The law is based on a strange observation that certain digits appear more regularly than others in data sets Durtschi et al (2004), conducted a first digit analysis on cheque amounts drawn to office supplies and insurance refund accounts in a large medical centre. Cheque amounts drawn to office supplies account did not conform

to Benford's Law but on further scrutiny, the payment were legitimate. A first digit test of insurance refund accounts did not conform to Benford's Law. A detailed inspection was done and discovered that more refund was disbursed and hence the test indicated a fraud. Therefore, digital analysis based on Benford's Law can effectively be used but the auditors should be watchful as non-compliance may not confirm a fraud.

Evidently, different authors draw diverse conclusion from the application of Benford`s Law in fraud detection. There are no studies that have been done to determine if Benford`s Law can be used to detect fraud in SACCOs in Kenya. This study seeks to bridge the gap and ascertain if auditors can use Benford`s to detect fraud in SACCOs in Kenya.

2.3.3 Authors with partial support on Application of Benford's Law in Fraud Detection

Ozer and Babacan (2013) used the Digital Analysis methodology to study effectiveness of Benford's Law. They examined annual off-balance sheet disclosures of Turkish Banks over the period 1990-2010 and tested whether results of digital analysis conforms the expected fraud and manipulation level realized in Turkish Banking System. Their finding provided partial support for the idea that Digital Analysis could be applied as a statistical audit tool in order to determine the fraud and manipulations. First, as it is expected, Digital Analysis suggests no fraud and manipulation regarding 2000-2010 period. However, it was inadequate for the fraud and manipulations realized during the 1990-1998. The findings support the proposition that data set that complies with Benford Distribution does not confirm the authenticity and accurateness of that data set. However, the fact that a data set does not comply with Benford Distribution is enough to be suspicious about that data set.

The consensus has been that just as people are poor at producing random data, they are poor at producing data that fits to Benford's Law. However, Diekmann's (2007) data challenged this conclusion. He first showed that unstandardized regression coefficients reported in journals were a good fit to Benford's Law. He then asked students in sociology or economics to fabricate multiple four-digit "plausible values" of regression coefficients that would support a hypothesis. He found a reasonable fit to Benford's Law. His results were in agreement with the finding by Mosimann *et al.* (2002) that the inspection of the rightmost digits in fabricated data provides better clues to errors or data fabrication than does the inspection of the first digit. Subjects favor smaller first digits in fabricating regression

coefficients, resulting in a Benford-like pattern for the distribution of first-digits in fabricated data. So, a test for the fabrication of regression coefficients might most fruitfully focus on the second, third or later digits. If second and later digits deviate from the Benford distribution, this deviation may yield an indication that the data have been fabricated. At least for regression coefficients, it appears that using a Benford test of first digits for data fabrication would provide misleading results.

2.3.4 Conditions of Benford's Law

Benford's Law does not apply universally. To enhance the reliability of the results, datasets to be analysed by Benford's Law must satisfy several conditions. Benford (1938) and Nigrini (2009) suggest that candidate datasets must possess the following characteristics: Numeric data. Benford estimates the expected frequencies of leading digits in numerical datasets.

Not restricted by maximums or minimums, the numbers should not be restricted by maximums or minimums meaning that the data set is not generated in a completely random fashion, but rather uses a restricted or manipulated set of digits as the potential leading digit,as the case of ATM card withdrawal, commonly in Kenya a minimum of one thousand and a maximum of thirty thousand. These limits result in the exclusion of certain numbers and, as a result, will skew the distribution of leading digits frequencies.

Not assigned numbers or invented numbers. The same is true if there is a formula or structure to the manner in which the number is generated. For example, Kenyan mobile telephone numbers are assigned with a four digit prefixes which are specific to service provider followed by six numbers which are the only truly randomly generated numbers in a phone number. Assigned numbers can be allocated in any predetermined order. Consequently, the distribution of leading digits in assigned numbers will be biased toward certain digits

Simkin (2010) recommends data sets of at least 100 records. The forensic auditor should be careful in extracting a sample and then using Benford's Law on the sample. The magnitude of the sample is important in terms of the accuracy of the Digital Analysis. Generally, as the number of the data increases, the analysis will give better results (Hales et al., 2008). Hales et al. (2008) stated that the Digital Analysis gives good results on the big samples consisting of data over 500. Hales et al. (2008) proposed that successful results could also be obtained in

small samples consisting of 100 samples, however, successful results could not be obtained from samples consisting of 50 data.

Prices set below the psychological barriers for example Kes 199 is perceived to be less than 200,thus prices tend to cluster below psychological barriers. Thus, before applying Benford's Law, the forensic auditor should ensure that the numbers are randomly generated without any real or artificial restriction of occurrence.

Pinkham (1961) stated a premise that if indeed there was some law governing digital distributions, this law should be scale invariant. So if the world's island or the length of the world's rivers, it would be immaterial if these numbers were expressed in Kilometres (Square) or Miles (Square). Benford's Law is scale invariant, it does not matter which units is chosen for measurements be it in - kilometers, miles, feet, centimeters or others.

In this study, the above conditions have been complied with.

2.4 Elements of Fraud

Albrecht et al (2004) for fraud to occur, three elements come together to greatly enhance the chance for fraud in the workplace. The elements are: perceived pressure, opportunity and rationalization. Albrecht et al (2004) pressure is the key component of the fraud triangle with greater financial need there is greater pressure to perpetrate fraud. Non-financial pressures which may include the need to report better results than actual performance, frustration with work, or even a challenge to beat the system can also motivate fraud.

Albrecht et al (2004) argued that despite perceived pressure, fraud perpetrators must also have a perceived opportunity else, they will not commit fraud. With intense perceived pressures, executives who believe they will be caught and punished seldom commit fraud.Wheareas executives who believe they have an opportunity to commit and conceal fraud often give into their perceived pressures. Perceived opportunities to commit management fraud may include a weak board of directors or insufficient internal controls and the ability to conceal the fraud in complex transactions or related-party transactions. When controls are weak, employees have greater opportunities to commit fraud. These controls play an important role in preventing and detecting fraud and protecting the organization's resources.

Albrecht et al (2004) noted that fraudsters will have additional excuses or justification to explain their dishonest actions or to rationalize embezzlement as acceptable. The employee believes that his or her fraudulent act is only a loan -"I will pay it back" or a form of justice- "they owe it to me". Executives may rationalize their actions as "all companies use aggressive accounting practices" or "the problem is temporary and will be offset by future good results".

2.5 Factors Causing Fraud

Fraud for or against a company can take the form of fraudulent financial reporting, also known as management fraud, and misappropriation of assets or employee fraud, also known as defalcation. Due to the nature of auditing and its inherent limitations, fraud is very difficult to detect for a number of reasons. First, it may be committed by people who are familiar with accounting procedures and can cover it up. Another reason could be that auditors do not possess all the necessary skills to detect fraud and time pressure on auditors. In addition, there is built-in conflict since auditors are asked to investigate upper management who indirectly are the same group that hired them. Finally, by detecting fraud an auditor may well be facing the spectre of protracted litigation, grand juries, and trials, and one immediately sees why the auditor may hope the issue of fraud never sees the light of day (Krambia-Kapardis, 2002).

Motivating factors cited for the involvement of management in fraudulent financial reporting include compensation packages based on reported earnings. There is support in the literature for management compensation as a significant motivator of fraudulent financial reporting (eg, Watts and Zimmerman 1990, AICPA 1987), although there have also been contrary findings (Dechow et al 1996).

Another motivation factor is the desire to maintain or increase share prices and the need to meet internal and external forecasts. When a firm is failing to achieve targets, there is incentive for management to falsify financial reports to meet them and protect share prices (Feroz *et al.*, 1991; Dechow *et al*., 1996). The desire to minimise tax liabilities (Spathis 2002) and the need to avoid violations of debt covenants could motivate fraud. Dechow *et al* (1996) found that firms committing financial statement fraud had higher leverage than control firms.

Spathis (2002) mentions the need to meet unrealistic commitments made to creditors as a motivation to commit fraud. The Treadway Report (AICPA 1987) found that the desire to postpone dealing with financial problems (and thus violating debt covenants) was a frequent incentive for fraudulent financial reporting. Finally, the desire to raise external capital cheaply could motivate fraud in an organization.

Albrecht *et al* (2004) examined financial statement fraud from the perspective of prevailing theories of management. They identify nine factors which together create the "perfect fraud storm": a booming economy (which hid the fraud), moral decay, misplaced executive incentives, unachievable expectations of the market, pressure of large borrowings, US rules-based accounting, opportunistic behaviour of audit firms, greed on the part of a wide variety of groups of people and educator failures. These nine factors are analysed by reference to the fraud triangle of pressure to commit fraud, opportunity to commit fraud, and inclination to rationalise fraud. They are also examined against agency and stewardship theories. Albrecht *et al* conclude from their analysis that managers who identify with a stakeholder perspective rather than with an agency theory perspective are less likely to commit fraud.

Loebbecke *et al* (1989) designed a fraud prediction model based on conditions in the entity, manager motivation and manager attitude. Bell and Carcello (2000) used the same fraud sample as Loebbecke *et al* and contrasted it with a non-fraud sample in order to consider the presence or absence of "red flags" as assessed by auditors. Some organisational factors identified as likely contributors to fraudulent financial reporting include: weak control environment; rapid growth; inadequate or inconsistent profitability; management placing undue emphasis on meeting earnings forecasts; and ownership status (public or private companies).

Fama and Jensen (1983) hypothesise that the internal control function of the board of directors is increased by the inclusion of outside directors, who have an incentive to develop reputations as experts in decision control. Jensen (1993) argues that outside directors have a greater incentive to monitor top management when they hold substantial amounts of shares. Beasley (1996) found that certain characteristics of outside directors, such as the percentage of equity held, help reduce the incidence of financial statement fraud.

Audit committees form an important part of the internal control environment. Young (2000) describes the audit committee as the vanguard in the prevention and detection of financial statement fraud. However, Beasley (1996) found that the existence of audit committees does not significantly affect the likelihood of the occurrence of financial statement fraud. This may be attributed in part to the number of times the audit committee meets. Beasley found that in 35% of fraud firms and 11% of non fraud firms in the research an audit committee had not met during the year. Dechow *et al* (1996) found that firms subject to fraud are less likely to have an audit committee.

Beasley *et al* (2000b) investigated corporate governance differences in a sample of fraud and non-fraud firms. They found that fraud firms were less likely to have an audit committee. Where one existed in a fraud firm, it tended to be less diligent and less independent; non-fraud firms had more outside directors on the audit committee than fraud firms. They also found that internal audit departments were less common in fraud firms.

According to Khanna & Arora (2009), highlighted that overburdened staff, low compliance level and lack of training as the causes of bank frauds.Chiezey & Onu (2013) noted that most frauds are caused by staff involvement in frauds. Idowu (2009) did an assessment of fraud and its management in Nigeria Commercial Banks. The study revealed that greed rather than poor salaries is what makes people to commit fraud. Okoye and Gbegi (2013) carried out a study on the evaluation of the effect of fraud and related crimes on the Nigerian Economy. The study revealed that, weak internal controls increase the chances of fraud. Idolor (2010) in his research on Bank Frauds in Nigeria, found out that poor remunerations, lack of proper staff training and lack of proper background check on staff as some of the causes of frauds. According to Akinyomi (2012), greed is the foremost cause of fraud in his study on the examination of fraud in the Nigerian Banking sector and its prevention.

Fraud in Kenya has been on the rise in the past. According to PWC, annual crime report of 2014 in Kenya, one in every two respondent had experienced fraud in the last two years. It affected mostly financial institutions resulting to heavy losses. According to Anti- Banking Fraud Investigations Department (2013), financial institutions in Kenya lost Kshs 1.6 billion between January and September 2013 which was partly attributed to lack of punitive measures in the judicial system and reluctance of the regulators. Mahinda (2012) did a study on determinants of occupational fraud in Commercial Banks in Kenya. The study revealed

that characteristics of Bank employees affect the occupational fraud. According to Githecha (2013) on his study on the effect of fraud risk management strategies on the financial performance of Commercial Banks in Kenya, the banks should adopt fraud management strategies to reduce financial fraud losses in order to enhance growth in financial performance so as to maximize the bank value. In Kenya, most studies have concentrated in the Banking Sector and the causes of fraud have been identified as to emanate from employees perspective. This leaves a wide knowledge gap that this study seeks to bridge by finding out the specific causes of fraud in SACCOs in Kenya.

2.6 Characteristics of financial statement fraud

According to Rosplock (2001) ,intent to conceal and take advantage by suppressing the truth of assets, liabilities, cashflows, sales and profitability is creating a new level of risk for organizations. He further reveals that in companies in high risk categories of fraud in financial reporting, they are affected by weak solvency(liquidity ratio),high leveraged conditions and overcapitalization. Weak efficiency shows in slow turnover of trade debtors, trade creditors and stocks; or in a substantially inadequate cashflow or working capital to sustain growth and minimal or nil profitability.

Beasley et al. (1999) examined 204 cases of financial statement fraud, under investigation at the time by Securities and Exchange Commission (sec).

Some of the key findings were: Most of the small companies(noted as fraudulent) were not listed in the New york securities, the mean fraud period extended over 23.7 months. Over 14 % of 204 of the companies engaged in fraud over a period less than an year meaning that fraud overlap at least two financial periods, most audits had no audit committees, most audit committees rarely met, most companies' boards were dominated by insiders and had outsiders with significant equity ownership and apparently little experience of serving as directors of the company; whereas audit boards require analytical procedures to improve financial statement fraud, changes in behaviour or lifestyle that may indicate assets have been misappropriated, further, the committee of sponsoring organizations of tread way commission(COSO) defined financial statement fraud as intentional or reckless conduct, whether by act of omission, which result in materially misleading financial statement; where the founders and the board members own a significant portion of the companies, in nearly

40% of the companies, authorizations for vote by proxy provided evidence for family relationships among directors and officers. The current founder and Chief Executive Officer were the same person, or the original Chief Executive Officer was still around in nearly half the companies; severe consequences were evident when companies were involved in fraud, bankruptcy, significant changes in ownership and suspension from trading in national exchanges; account receivable and inventory were the two mostly misstated asset accounts followed by property plant and equipment, loans or notes receivables, cash, investments, patents and natural resources.

The above findings of Beasley et al, although they involve small companies other than SACCOs, set a basis to this research. As a matter of fact in Kenya, no SACCO has been listed in the Nairobi Securities Exchange, which ties well with study of Beasley et al.

2.7 Techniques and approaches used to detect fraud

According to The Institute of Internal Auditors (2001) fraud examiners commonly employ the comparative techniques to identify the relationships among the financial data that do not appear reasonable. The comparison involves comparing current period information with similar information from prior periods. Prior period amounts normally are assumed to be the expectation for the current period. A modification of this comparison is the incremental approach whereby prior period numbers are adjusted for known changes, such as significant purchases or sales of assets and changes in lines and volumes of business.Comparison of current period information with budgets or forecasts should be reasonable as well.

Cash flow analysis- cash flow statement reports how money flows into and out of the company justifiably. The statement of cash flows details the sources and uses of the company's cash (ACFE,2014).

Financial Ratio analysis is a means of measuring the relationship between two different financial statement amounts. Ratios are calculated from current year numbers and are then compared to previous years, other companies, the industry, or even the economy to judge the performance of the company. This form of financial statement analysis is very useful in detecting red flags for a fraud examination. Ratio analysis allows for internal evaluations

using financial statement data. The relationship and comparison are the keys to the analysis. Current Ratio and Quick Ratio are common ratios analysed.There are only a few ratios that can be used to detect fraud in SACCOs (Lari,2009)

An interview is a question and answer session designed to elicit information. It differs from an ordinary conversation in that an interview is structured, free-form and is designed for a purpose (ACFE,2014).People in organisations who have both motive and opportunity are the prime candidates fraudulent misstatement hence interviewed.

Review of complaints, whistle blows, tips and hotline registers is the most common method of initial fraud detection (ACFE,2014).In a study by PWC (2007), whistleblowers were responsible for 43% of the fraud detection. PWC(2007) and ACFE(2014),in agreement concluded that occupational frauds are much more likely to be detected by a tip then by audits, controls or any other means. Significantly, the ACFE found that 46.2% of all frauds were uncovered by tipsters, while only 3.2% was detected by law enforcement. These statistics are remarkably similar to the PWC findings. The ACFE also recognized the contributions of whistleblowers and strongly endorsed corporate cultural changes designed to encourage whistleblowers. The study concluded that since over half of all fraud detection tips came from employees, they should be encouraged to report illegal or suspicious behavior, and they should be reassured that reports may be made confidentially and that the organization prohibits retaliation against whistleblowers.

According to Pinkasovitch(2011) there are traditionally two methods of percentage analysis of financial statements: vertical analysis and horizontal analysis. Vertical analysis is a technique for analyzing the relationships between the items on any one of the financial statements in one reporting period. The analysis results in the relationships between components expressed as percentages that can then be compared across periods. This method is often referred to as “common sizing” financial statements. In the vertical analysis of an income statement, net sales is assigned 100%; for a balance sheet, total assets is assigned 100% on the asset side, and total liabilities and equity is expressed as 100% on the other side. All other items in each of the sections are expressed as a percentage of these numbers

Pinkasovitch(2011) describes horizontal analysis is a technique for analyzing the percentage change in individual financial statement items from one year to the next. The first period in the analysis is considered the base, and the changes in the subsequent period are computed as a percentage of the base period. If more than two periods are presented, each period's changes are computed as a percentage of the preceding period. The resulting percentages are then studied in detail. It is important to consider the amount of change as well as the percentage in horizontal comparisons. A 5% change in an account with a very large dollar amount may actually be much more of a change than a 50% change in an account with much less activity. Like vertical analysis, this technique will not detect small, immaterial frauds. However, both methods translate changes into percentages, which can then be compared to highlight areas of top concern

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the methods and procedures that were applied to achieve the set objectives of the study. They include a description of the research design, target population, data collection methods, data analysis, research quality and ethical considerations.

3.2 Research Design

This study is consistent with the prior work of Saville (2006) and Lari (2009).It comprised of survey questionnaires to collect primary data from SACCOs. Secondary data was also sought to supplement primary data collected through questionnaires.

3.3 Target Population and Sampling Frame

The target population was the SACCOs registered to operate in Kenya by the Ministry of Cooperative and Development. According to data from the Ministry, there were 5,000 SACCOs operating in Kenya. During the year 2009-2011, 18 SACCOs were investigated and confirmed to have fraud by being published in the Kenya gazette. A sample of 14 SACCOs with fraud was obtained from the population of the 18 SACCOs with fraud and a similar number of those where fraud had not been established were taken for comparison proportionately. This study utilized matched pair technique to obtain a sample of non-fraudulent SACCOs. The sample was carefully selected and matched proportionately to balance SACCOs with fraud and non-fraud ones based on asset base for the 2009-2011 for comparison purposes. This was in an effort to investigate on the ability of Benford's Law to give better or similar results as other fraud detection methods.

Table 3. 1: Target population versus sample obtained

	SACCOs WITH FRAUD	SACCOs WITHOUT FRAUD
Target Population	18	5000-18=4982
Sample	14	14/4982

3.4 Data Collection Methods

Primary data was collected through questionnaires. Drop and pick as well as online surveys methods were used to distribute 28 questionnaires in SACCOs that were selected.The method was used to enhance response rate and ensure respondents have ample time to respond to the questionnaires. This data was used to assess the factors causing fraud in Kenyan SACCOs, to analyse the characteristics of fraud in Kenyan SACCOs and to examine techniques used in Kenyan SACCOs.

Secondary data was collected from Ministry of Cooperative and Development records to supplement primary data collected through questionnaires. A list of SACCOs was obtained from the regulator. Data was obtained from the 14 SACCOs with fraud and a similar number of those where fraud had not been established were taken for comparison. SACCOs without fraud had unqualified audit reports. In total, data from 28 SACCOs was used in the study. The Data variables included all the line items of balance sheet, statement of changes in equity, income statements, appropriation account, cash flow statement, disclosures and notes in financial statements by SACCOs. These variables were used by Lari (2009) to determine ratios that are significantly capable of detecting fraud. The focus was on the first digit of each entry. This data was used to investigate the application of Benford's Law for fraud detection in SACCOs data.

3.5 Data Analysis

Descriptive statistics were used for quantitative and qualitative data analysis respectively. Descriptive statistics included mean scores, percentages and frequencies. Results of quantitative data analysis were presented in charts and tables while results of qualitative data analysis were presented in prose or narrative form with the highest means of the scale being main determinants of factors causing fraud, characteristics of fraud and the fraud detection techniques used in Kenyan SACCOs.

Chi square test was utilized in the study to analyse secondary data. The chi square test have been used by Durtschi et al (2004), Nigrini (1996) and Hill (1996) to compare the frequencies observed and expected. Chi-square is a statistical test commonly used to compare observed

data with data expected to be obtained according to a specific hypothesis. The formula for calculating chi-square (χ^2) is:

$$\chi^2 = \sum \frac{(o-e)^2}{e}$$

That is, chi-square is the sum of the squared difference between observed (o) and the expected (e) data (or the deviation, d), divided by the expected data in all possible categories. Chi-square distribution table was used to determine significance of the value.

i) Determine degrees of freedom and locate the value in the appropriate column.

ii) Locate the value closest to your calculated χ^2 on that degrees of freedom *df* row.

iii) Move up the column to determine the p value.

To investigate the frequency of the first digit, the leading digit of all the data variables in the line items of balance sheet, statement of changes in equity, income statements, appropriation account, cash flow statement, disclosures and notes in financial statements per SACCO was binned into nine bins of 1 to 9. A frequency comparison test was done by use of a chi-square, on the counts. The expected frequency was Benford's Law whereas the binned data became the observed data. The set of SACCOs which did not have fraud was expected to follow Benford's Law and the set which had fraud was not expected to follow Benford's Law because of human bias and intervention during fraud perpetration.

At 5% confidence level, the below hypothesis was used to determine if Benford's Law can be used to detect fraud in SACCOs in Kenya.

H_0 : Benford's Law can be used to detect fraud in Kenyan SACCOs by auditors.

H_1 : Benford's Law cannot be used to detect fraud in Kenyan SACCOs by auditors.

3.6 Research Quality

The research instruments comprised of a semi-structured questionnaire. The reliability and validity of the research instrument was computed and maintained throughout the study.

3.6.1 Reliability of Research Instrument

Reliability of an instrument is the measure of the degree to which a research instrument yields consistent results or data after repeated trials. This was achieved by maintaining a totally transparent, systematic approach of data processing which was documented.

3.6.2 Validity of Research Instrument

According to Paton (2002) validity is quality attributed to proposition or measures of the degree to which they conform to establish knowledge or truth. Mugenda and Mugenda (1999) defined validity as the accuracy and meaningfulness of inferences which are based on research results

3.7 Ethical Considerations

The participants were informed of the purpose of the study and consent to participate in the study was sought. Confidentiality was guaranteed and maintained throughout the study by masking the identity of SACCO names. SACCOs without fraud were renamed as Non Fraud Financial Statements (NFFS) while those with fraud were renamed as Fraud Financial Statements(FFS).The SACCOs data documents were securely stored to enhance confidentiality. Permission was also sought from the relevant authorities and SACCOs where data was collected.

CHAPTER FOUR

DATA ANALYSIS AND INTERPRETATION

4.1 Introduction

This chapter presents data analysis and interpretation. Results from questionnaires distributed to SACCOs are presented. Entries of the two sets of SACCOs were studied. The entries comprised line items of balance sheet, statement of changes in equity, income statements, appropriation account, cash flow statement, disclosures and notes. The first set consisted of SACCOs with fraud while the second set consisted of SACCOs without fraud. An equal number of SACCOs from each category were studied and results are presented in this chapter. The response rate 100% for questionnaires and 77.7 for secondary data.

4.1.1 General Information

The majority of the respondents were Internal auditors (40.4%) and Risk managers (21.7%). External auditors were 25.4% of the respondents while Compliance managers and IT auditors were 7.4% and 5.1% respectively.

Table 4. 1: Position

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	IT auditors	2	5.1	5.1	5.1
	Compliance managers	2	7.4	7.4	12.5
	External auditors	7	25.4	25.4	37.9
	Risk managers	6	21.7	21.7	59.6
	Internal auditors	11	40.4	40.4	100.0
	Total	28	100.0	100.0	

Majority of the respondents 57.1% were found to have worked in the SACCO for 4-7 years. Respondents who had worked for 8-11 years were 17.9% while those who had worked for 0-3 years were 14.2%. Only 10.8% of the respondents had worked in the SACCO for 12 years and above.

Table 4. 2: Years worked in the SACCO

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0-3 years	4	14.2	14.2	14.7
	4-7 years	16	57.1	57.1	71.3
	8-11 years	5	17.9	17.9	89.2
	12 years and above	3	10.8	10.8	100.0
	Total	28	100.0	100.0	

Majority of the respondents (58.1%) indicated that they encountered fraud in their day-to-day work as compared to 41.9% who indicated they do not encounter fraud.

Table 4. 3: Encountered fraud in day-to-day work

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	15	55.1	58.1	58.1
	No	11	39.7	41.9	100.0
	Total	27	94.9	100.0	
Missing	System	1	5.1		
Total		28	100.0		

4.2 Factors Causing Fraud in Kenyan SACCOs

The respondents were asked to indicate the factors they thought have led to fraud in SACCOs. Most of the respondents cited poor internal control systems, lack of integrity, poor pay of SACCOs' employees and poor management information. Respondents also cited the availability of opportunity, poor technology and incompetence of staff.

In those SACCOs without fraud according to the respondents, it can be attributed to better internal control systems, closer monitoring and regulations by management, constant regulator audits and honesty among employees and management. The respondents also cited better salaries and transparency of the management.

Asked whether they have heard of fraud in other SACCOs, majority of the respondents (93.9%) indicated yes as compared to only 6.1% who indicated no.

Table 4. 4: Heard of fraud in other SACCOs

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	18	62.5	93.9	93.9
	No	1	4.0	6.1	100.0
	Total	19	66.5	100.0	
Missing	System	9	33.5		
Total		28	100.0		

In a scale of 1-5 where 1 was 'Not at all' and 5 was 'To a very great extent', respondents were asked to indicate their extent of agreement with a number of statements regarding factors causing fraud in SACCOs. According to the results, internal controls (M=4.19, SD=1.201) is factor that to a great extent causes fraud in SACCOs. Respondents indicated that targets or pressure to deliver where compensation packages are based on reported earnings (M=3.10, SD=.799) to a moderate extent causes fraud. Governance of the SACCO (M=2.86, SD=1.243), regulations by authorities (M=2.81, SD=.851) and the desire to raise external capital cheaply (M=2.69, SD=1.447) were established to cause fraud in SACCOs to a little extent.

Table 4. 5: Factors Causing Fraud

	N	Mean	Std. Deviation
Internal controls	17	4.19	1.201
Targets or pressure to deliver where compensation packages are based on reported earnings	19	3.10	.799
Governance of the SACCO	17	2.86	1.243
Regulations by authorities	19	2.81	.851
Desire to raise external capital cheaply	19	2.69	1.447
Valid N (listwise)	28		

4.3 Characteristics of Fraud in Kenyan SACCOs

The researcher asked respondents to rate how they agree with a number of statements in regard to recognizing fraud in SACCOs. The respondents were to use a scale of 1-5 where 1 is 'Not at all, 2 'Little extent', 3 'Moderate extent', 4 'Great extent' and 5 'To a great extent'. The results show that dubious entries in financial accounts (M=3.75, SD=1.172), cash flow problems (M=3.41, SD=1.065), change of lifestyle by employees (M=3.34, SD=1.447) and non-payment of suppliers (M=3.26, SD=1.135) moderately help in recognizing fraud in SACCOs. Restructuring of loan facilities (M=2.93, SD=1.374) to a little extent help in recognizing fraud in SACCOs.

Table 4. 6: Recognizing fraud in SACCOs

	N	Mean	Std. Deviation
Dubious entries in financial accounts	25	3.75	1.172
Cash flow problems	24	3.41	1.065
Change of lifestyle by employees	27	3.34	1.447
Nonpayment of suppliers	27	3.26	1.135
Restructuring of loan facilities	25	2.93	1.374
Valid N (listwise)	28		

4.4: Fraud detection and approaches used to detect fraud in Kenyan SACCOs

The study sought to establish from the respondents if they thought application of the fraud detection techniques and approaches would influence the detection results.From the analysis of the findings, it was noted that majority (71.4%) of the respondents indicated that, the application of the fraud detection techniques influenced effective detection of fraud in the financial statements while only a mere 28.6% of the respondents indicated that application of the fraud detection techniques would not influence effective detection

The respondents were asked to indicate fraud detection techniques/approaches used in SACCOs. Most of the respondents highlighted review of complaints, whistle blows, tips and hotline registers, financial ratio analysis, comparative techniques, cashflow analysis, vertical analysis and interviews.

The study sought to establish the level of agreement on the effectiveness of fraud detection based on the various techniques and approaches applied. The findings are illustrated in the table below as indicated

Table 4.8: Methods of Fraud detection

Techniques and Approaches of fraud detection	Frequency	Mean	Standard deviation
Comparative techniques-Comparison of current period information with similar information from prior periods	21	4.26	0.21
Cash flow analysis- cash flow statement reports how money flows into and out of the company justifiably	20	4.33	0.48
Interviews-People in organisations who have both motive and opportunity are the prime candidates fraudulent misstatement hence interviewed.	24	3.98	0.79
Review of complaints, whistle blows, tips and hotline registers	24	4.79	0.109
Vertical analysis is a technique, analyzes the relationships between the items on any one of the financial statements in one reporting period.	19	4.04	0.5489
In horizontal analysis, The first period in the analysis is considered the base, and the changes in the subsequent period are computed as a percentage of the base period	17	3.61	0.45
Computation of financial Ratio analysis	22	4.01	0.53

Based on the responses from the respondents, it was clear that most respondents agreed to a large extent that a review of complaints, whistle blows, tips and hotline registers gave a higher chance fraud detection. This inference was realised due to the high mean value calculated of 4.79. The standard deviation (.109) was in support of the study as it indicated little variation from the mean mark. It was established from the analysis that most respondents agreed to a very large extent on Cash flow analysis as an effective- cash flow. This was established by the high mean value calculated of 4.33.The small standard deviation calculated indicates uniformity in the responses from the respondents. It was also established that Comparison of current period information with similar information from prior periods was seen true by the high mean value calculated in the analysis of 4.26. The standard deviation calculated in the analysis of 0.21 indicated little variance from the mean mark in the responses. From this analysis it was clear that the technique and approach of fraud detection had a significant influence on effectiveness of fraud detection in financial statements in Kenyan SACCOs.

4.4 First Digit Analysis for SACCOs with Fraud

Based on this study finding,some entries for SACCOs with fraud followed Benford's Law contrary to conventional beliefs. Both SACCOs with a low number of entries and those with a higher number of entries exhibited a similar trend. Depending on the number of entries that the SAACCOs have, they were categorized into low, medium and high. SACCOs with entries that were below 300 were placed under low category while those with 301 to 500 entries were categorized as medium. SACCOs with 501 and above entries were categorized as high. This is illustrated by first digit analysis of the following SACCOs:

4.4.1 SACCOs with a high number of entries

SACCOs with a high number of entries demonstrated a trend that follows Benford's Law as shown by entries analyzed from FFS1 SACCO, FFS2 SACCO and FFS3 SACCO.

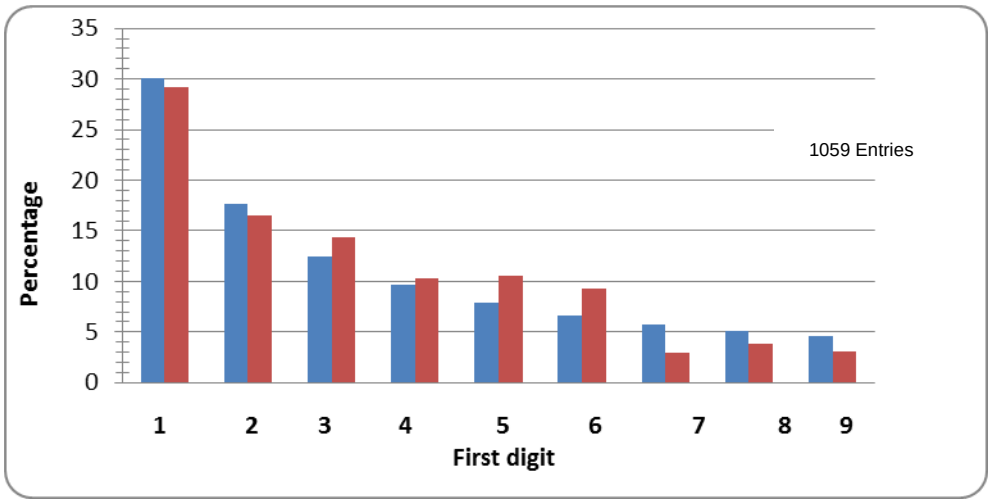


Figure 4. 1: Benford`s Law Vs FFS1 SACCO

Benford`s law distribution Sacco distribution

The results show that FFS1 SACCO entries closely followed Benford's Law.

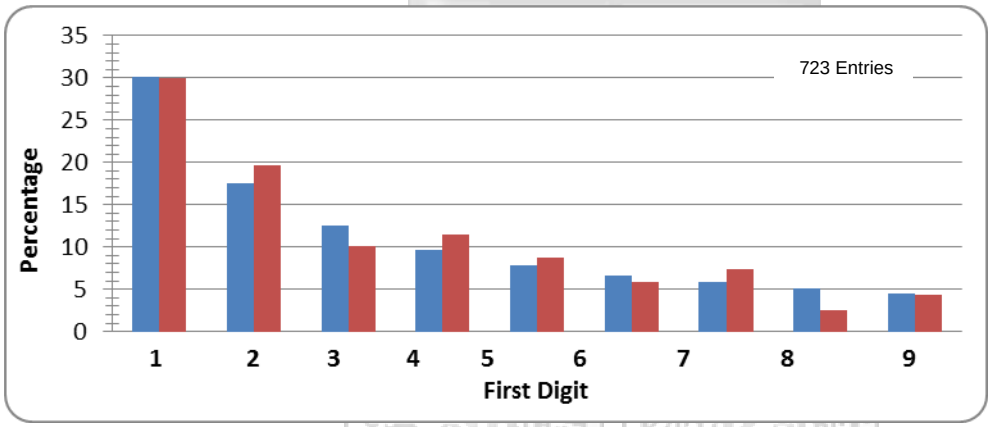


Figure 4. 2: Benford`s Law Vs FFS2 SACCO

The results show that FFS2 SACCO entries closely followed Benford's Law.

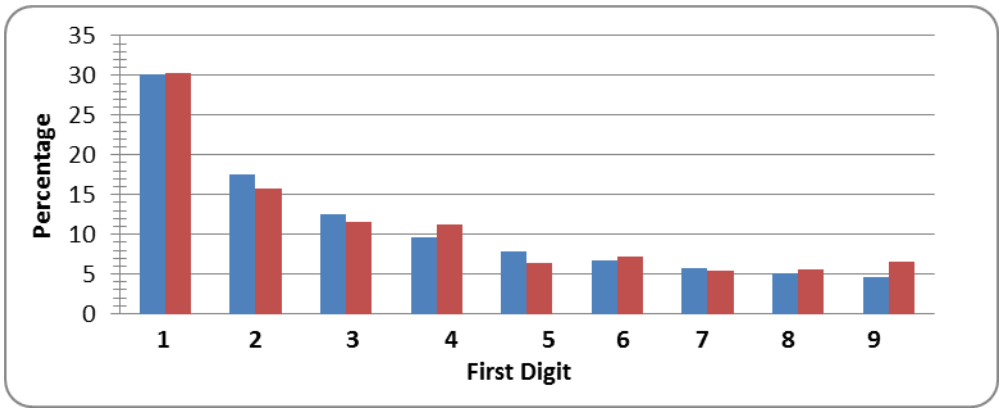


Figure 4. 3: Benford`s Law Vs FFS3 SACCO

The results show that FFS3 SACCO entries closely followec Law.

4.4.2 SACCOs with medium number of entries

SACCOs with a medium number of entries demonstrated a trend that follows Benford's Law as shown by entries analyzed from FFS4 SACCO, FFS5 SACCO, FFS6 SACCO, FFS7 SACCO, FFS8 SACCO, FFS9 SACCO, and FFS10 SACCO.

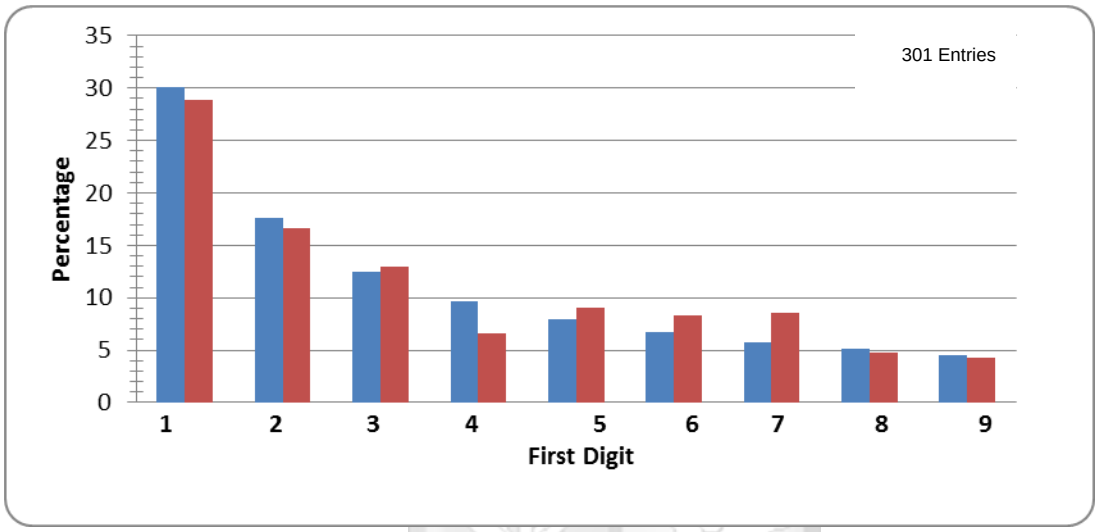


Figure 4. 4: Benford`s Law Vs FFS4 SACCO

The results show that FFS4 SACCO entries closely followed Benford's Law.

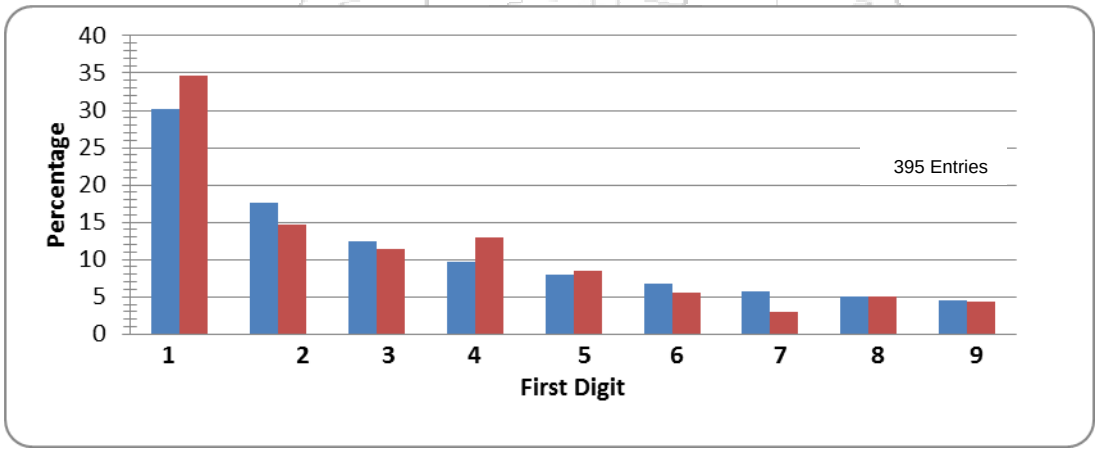


Figure 4. 5: Benford`s Law Vs FFS5 SACCO

The results show that FFS5 SACCO entries closely followed Benford's Law except where 1 and 4 were the first digits.

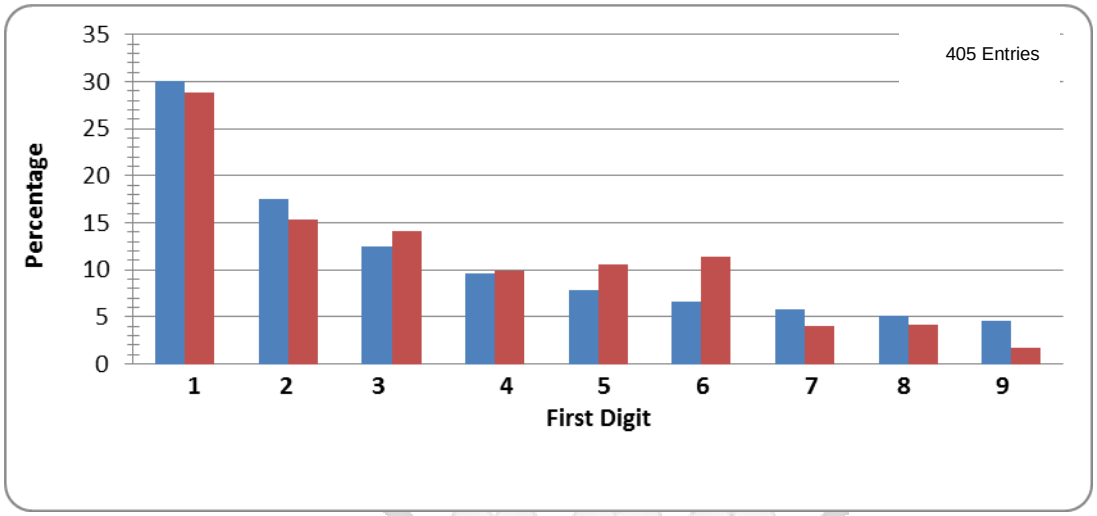


Figure 4. 6: Benford`s Law Vs FFS6 SACCO

The results show that FFS6 SACCO entries closely followed Benford's Law except where 5,6 and 9 were the first digits.

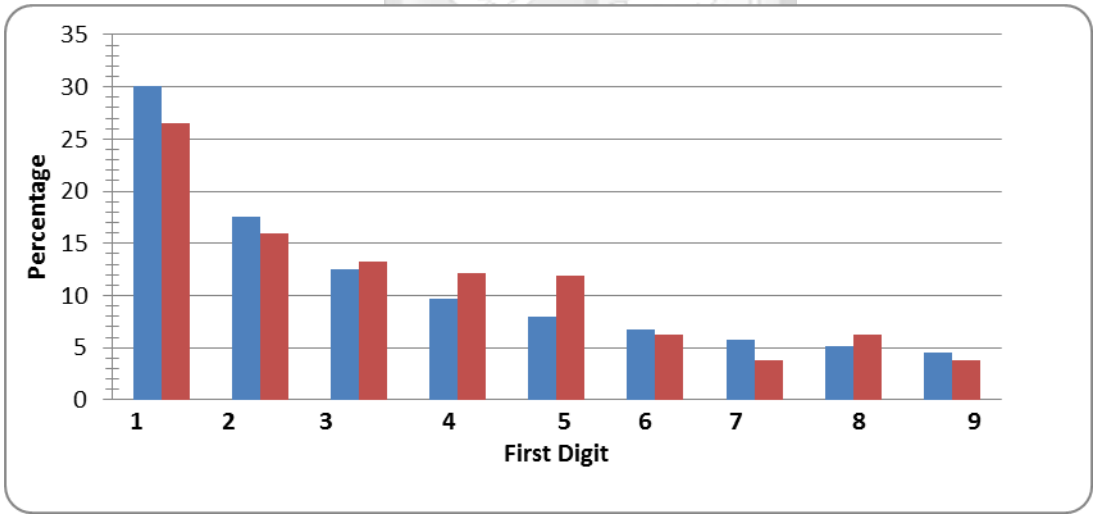


Figure 4. 7: Benford`s Law Vs FFS7 SACCO

The results show that FFS7 SACCO entries closely followed Benford's Law.

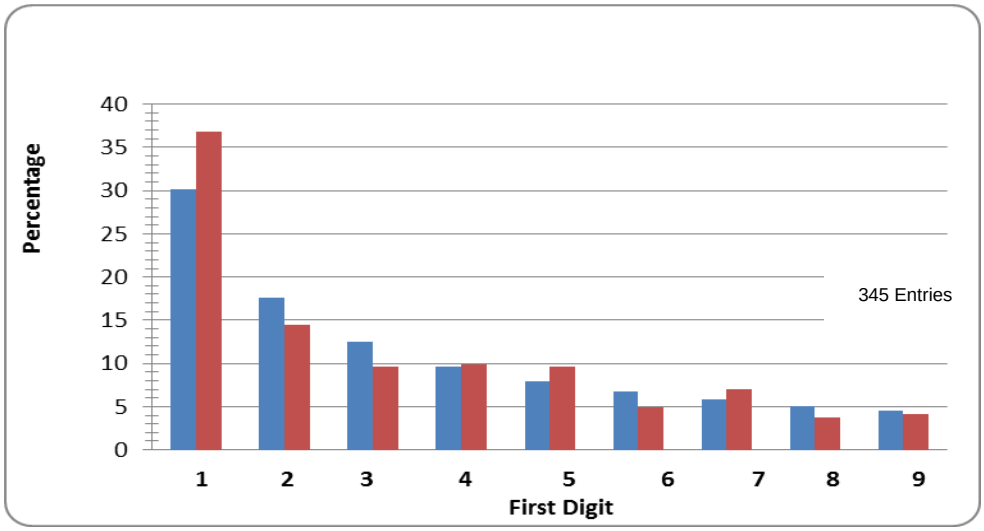


Figure 4. 8: Benford`s Law Vs FFS8 SACCO

The results show that FFS8 SACCO entries closely followed Benford's Law except where 1 was the first digit.

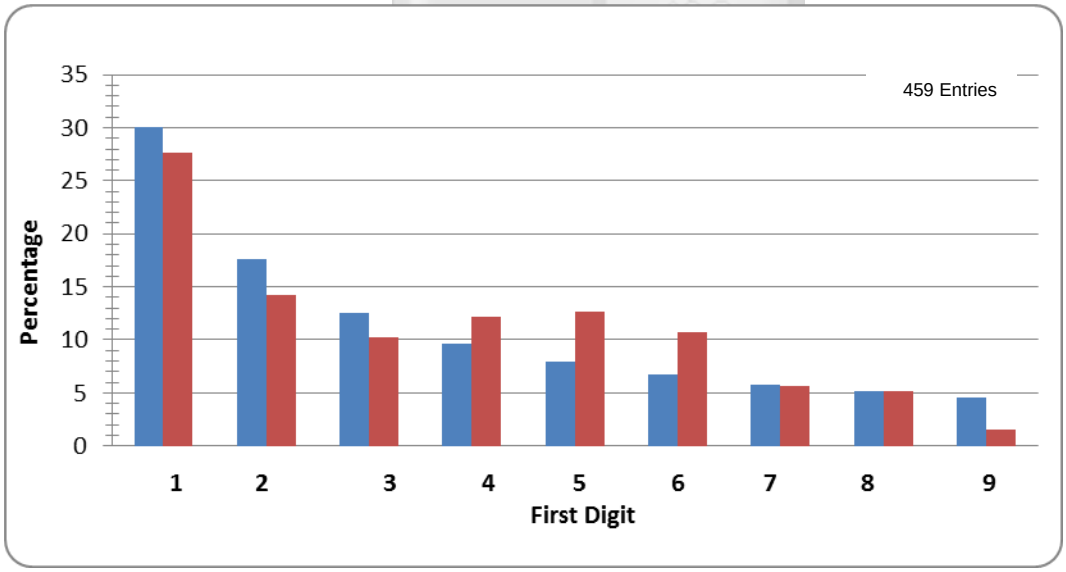


Figure 4. 9: Benford`s Law Vs FFS9 SACCO

The results show that FFS9 SACCO entries closely followed Benford's Law.

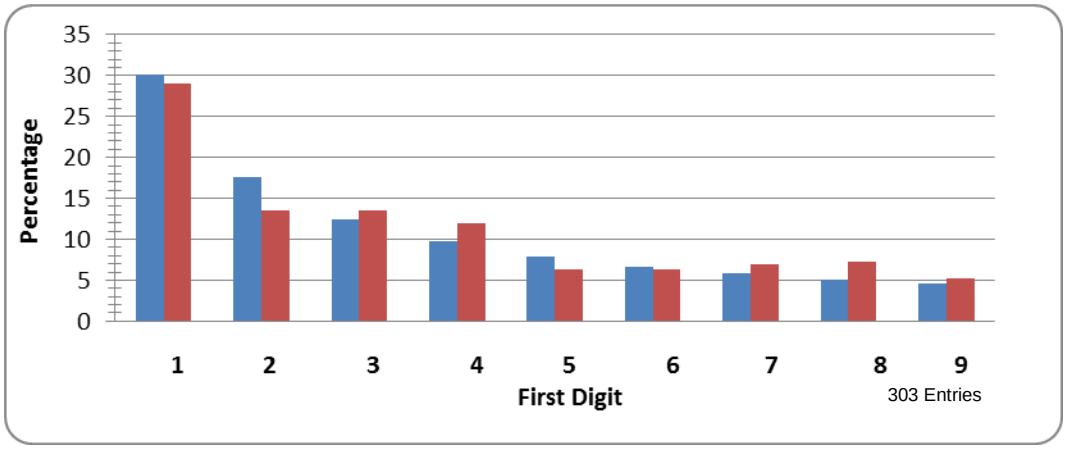


Figure 4. 10: Benford`s Law Vs FFS10 SACCO

The results show that FFS10 SACCO entries closely followed Benford's Law.

4.4.3 SACCOs with low number of entries

SACCOs with a low number of entries demonstrated a trend that follows Benford's Law as shown by entries analyzed from FFS11 SACCO, FFS12 SACCO, FFS13 SACCO, and FFS14 SACCO.

Table 4.9: First Digit Analysis for FFS11 SACCO

	Observed N	Expected N	Residual
1	48	60.2	-12.2
2	23	35.2	-12.2
3	32	25.0	7.0
4	28	19.4	8.6
5	22	15.8	6.2
6	28	13.4	14.6
7	8	11.6	-3.6
8	8	10.2	2.2
9	3	9.15	-6.15
Total	200		

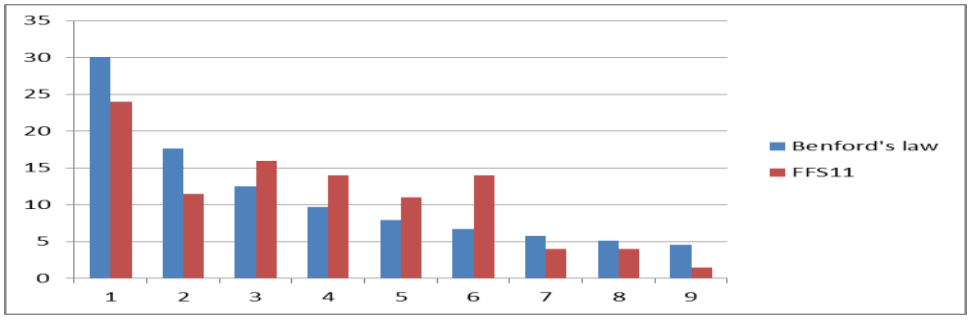


Figure 4. 11: Benford`s Law Vs FFS11 SACCO

See appendix II-FFS11

The results show that FFS11 SACCO entries did not closely followed Benford's Law.

Table 4.10: First Digit Analysis for FFS12 SACCO

	Observed N	Expected N	Residual
1	107	86.4	20.6
2	42	50.68	-8.68
3	30	35.98	-5.98
4	25	27.91	-2.91
5	25	22.8	2.2
6	19	19.28	-0.28
7	20	16.7	3.3
8	12	14.73	-2.73
9	8	13.17	-5.17
Total	297		

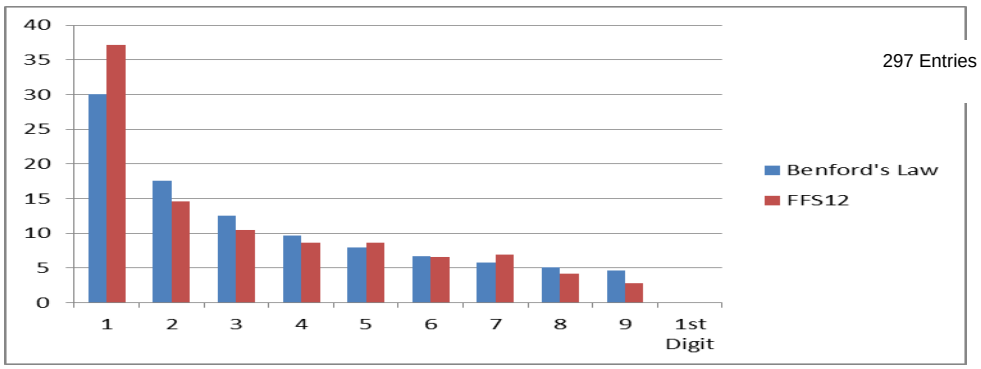


Figure 4. 12: Benford`s Law Vs FFS12 SACCO

See appendix II-FFS12

The results show that FFS12 SACCO entries followed Benford's Law except where 1, 7 and 9 are the first digits.

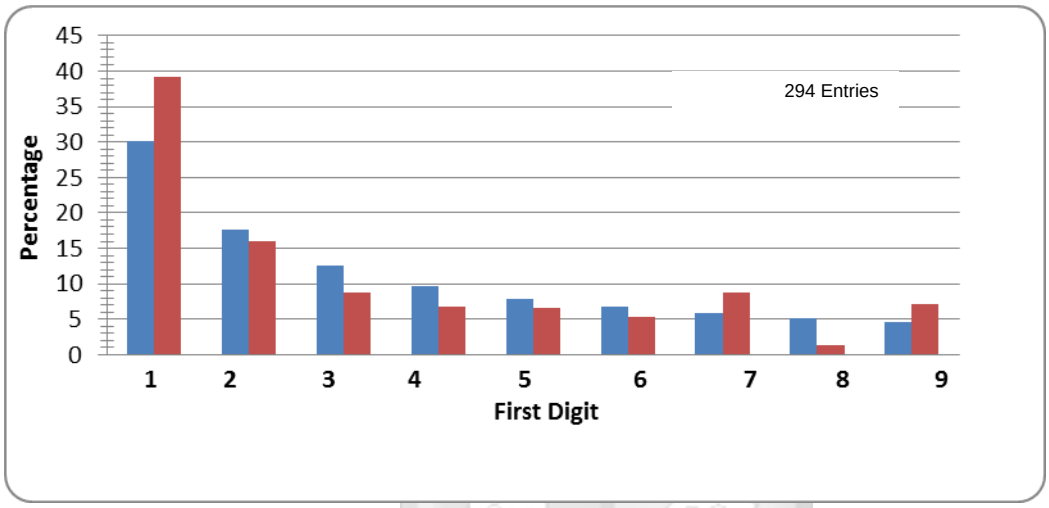


Figure 4. 13: Benford`s Law Vs FFS13 SACCO

The results show that FFS13 SACCO entries closely followed Benford's Law except where 1, 7, 8 and 9 are the first digits.

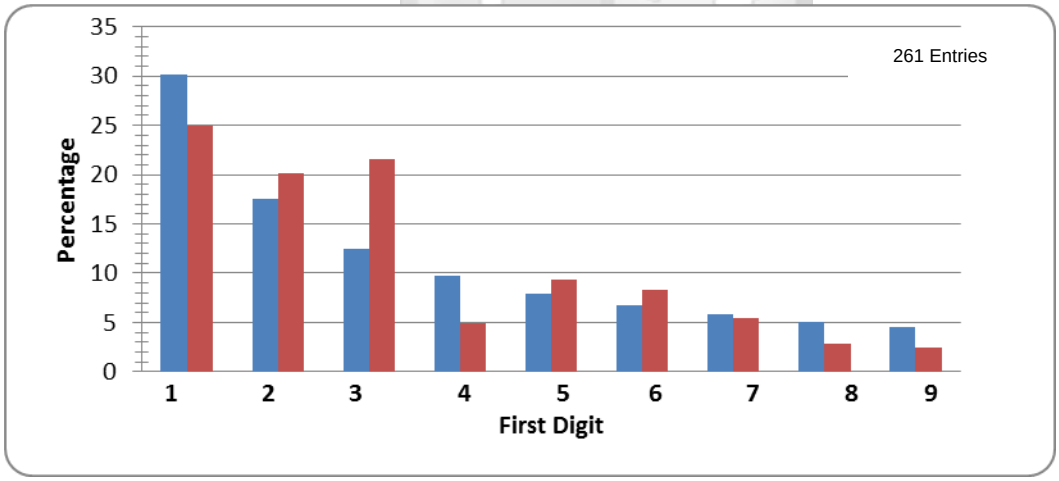


Figure 4. 14: Benford`s Law Vs FFS14 SACCO

Figure 4.14 shows a comparison of FFS14 SACCO entries and Benford's Law. The results show that FFS14 SACCO entries closely followed Benford's Law except where 2, 3 and 4 are the first digits.

Table 4.11: SACCOS with Fraud Statistical Summary

SACCO	P-VALUE	CHI SQUARE	DECISION
FFS1	0.00	48.309[a]	A
FFS2	0.005	22.217[a]	A
FFS3	0.124	12.655[a]	R
FFS4	0.327	9.185[a]	R
FFS5	0.052	15.393[a]	R
FFS6	0.00	29.066[a]	A
FFS7	0.013	19.373[a]	A
FFS8	0.071	14.453[a]	R
FFS9	0.00	41.975[a]	A
FFS10	0.295	9.589[a]	R
FFS11	0.00	35.434[a]	A
FFS12	0.138	12.305[a]	R
FFS13	0.00	32.859[a]	A
FFS14	0.001	25.903[a]	A

A= Accept hypothesis

R= Reject hypothesis

Out of 14 SACCOs that had fraud, Benford's Law could accurately predict fraud in only eight SACCOs which is 57.14%. Hence, Benford's Law can be used to detect fraud in SACCOs.

4.5 First Digit Analysis for SACCOs without Fraud

First digit analysis of entries from SACCOs without fraud followed Benford's Law as expected. This was established across SACCOs with low number of entries as well as those with high number of entries.

4.5.1 SACCOs with low number of entries

First digit analysis of entries from NFFS1 SACCO, NFFS1 SACCO, NFFS1 SACCO and NFFS1 SACCO are presented below. These SACCOs with entries below 300 were considered to have low number of entries.

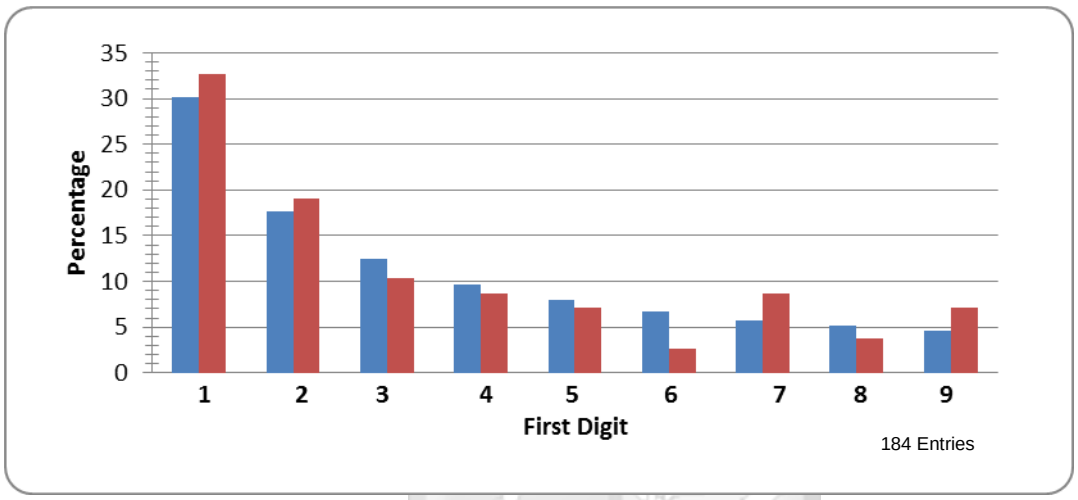


Figure 4. 15: Benford`s Law Vs NFFS1 SACCO

Figure 4.15 shows a comparison of NFFS1 SACCO entries and Benford's Law. The results show that NFFS1 SACCO entries closely followed Benford's Law.

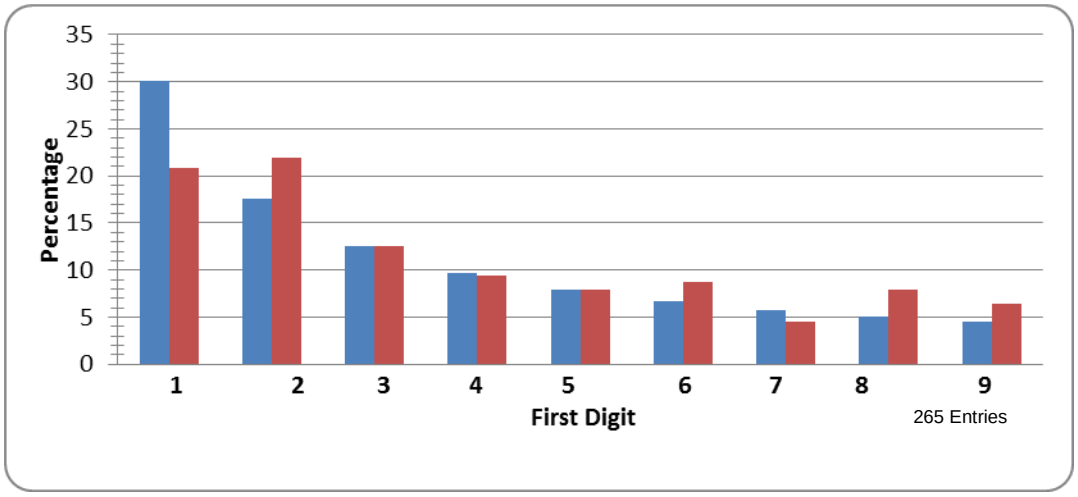


Figure 4. 16: Benford`s Law Vs NFFS2 SACCO

Figure 4.16 shows a comparison of NFFS2 SACCO entries and Benford's Law. The results show that NFFS2 SACCO entries did not follow Benford's Law except digits 3,4, and 5.

Table 4.12: First Digit Analysis for NFFS03 SACCO

	Observed N	Expected N	Residual
1	45	58.7	-13.7
2	34	34.33	-0.33
3	25	24.36	0.64
4	17	18.89	-1.89
5	27	15.44	11.56
6	16	13.055	2.945
7	8	11.3	-3.3
8	16	9.974	6.026
9	7	8.92	-1.92
Total	195		

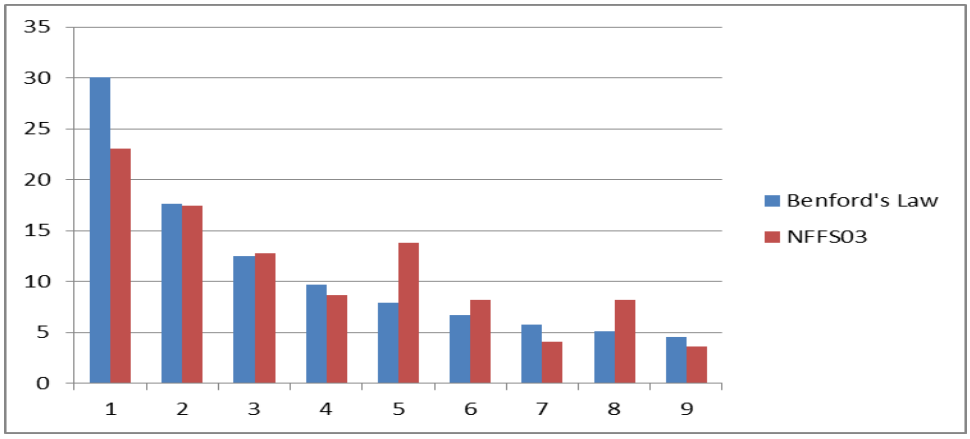


Figure 4. 17: Benford`s Law Vs NFFS3 SACCO

See appendix II-NFFS03

Figure 4.17 shows a comparison of NFFS03 SACCO entries and Benford's Law. The results show that NFFS3 SACCO entries closely followed Benford's Law xcept where 1, 5 and 8 are the first digits.

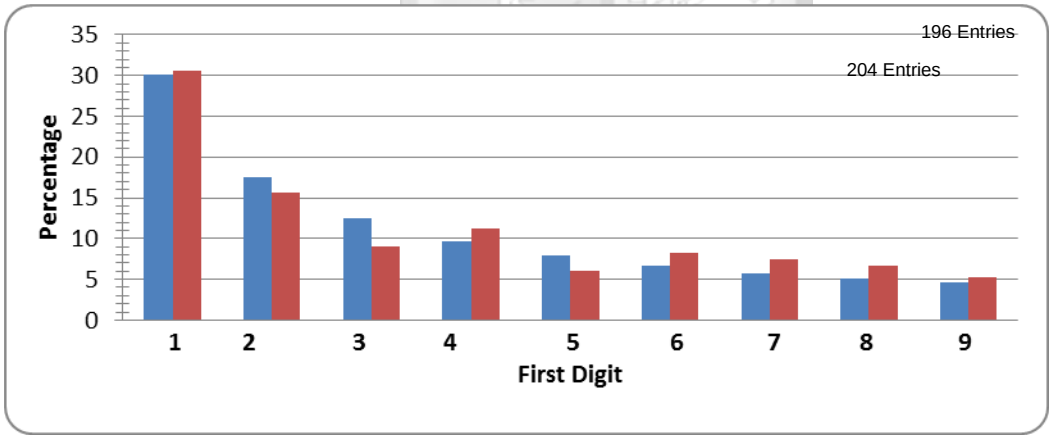


Figure 4. 18: Benford`s Law Vs NFFS4 SACCO

Figure 4.18 shows a comparison of NFFS4 SACCO entries and Benford's Law. The results show that NFFS4SACCO entries closely followed Benford's Law.

4.5.2 SACCOs with medium number of entries

Entries for SACCOs with medium number of entries in the category of SACCOs without fraud followed Benford's Distribution except NFFS5 SACCO. This is evident from the

following SACCOs; NFFS6 SACCO, NFFS7 SACCO, NFFS8 SACCO, NFFS9 SACCO, NFFS10 SACCO, and NFFS11 SACCO.

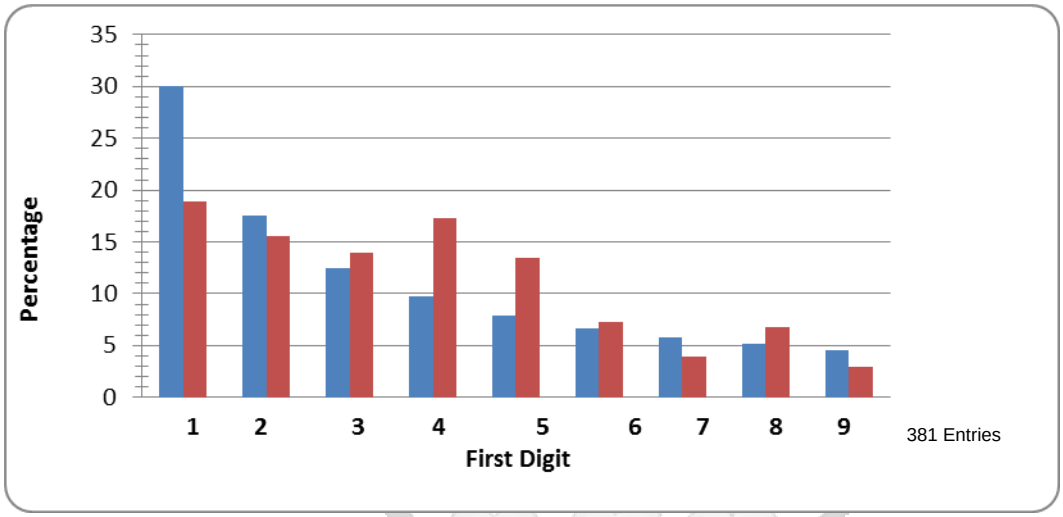


Figure 4. 19: Benford`s Law Vs NFFS5 SACCO

Figure 4.19 shows a comparison of NFFS5 SACCO entries and Benford's Law. The results show that NFFS5 SACCO entries did not follow Benford's Law except in the first digits.

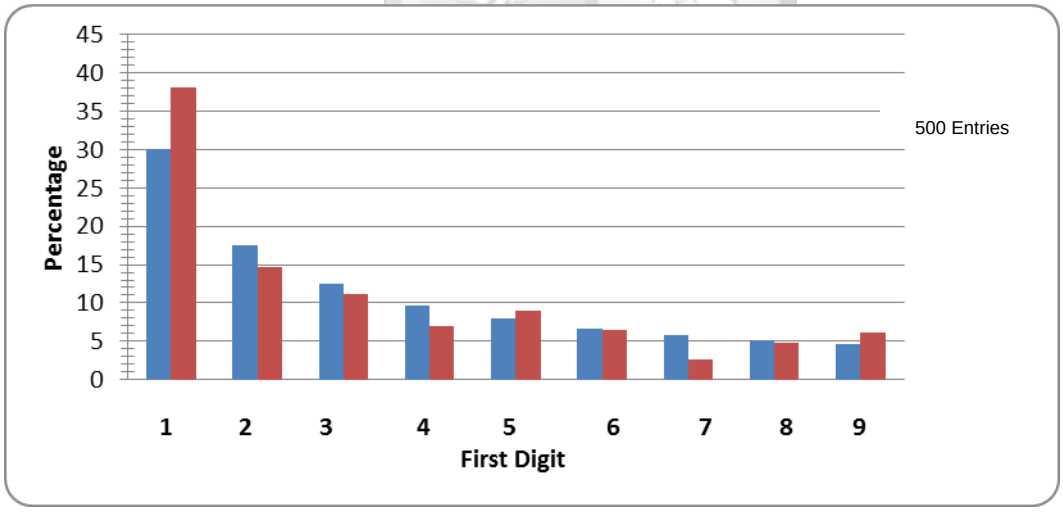


Figure 4. 20: Benford`s Law Vs NFFS6 SACCO

Figure 4.20 shows a comparison of NFFS6 SACCO entries and Benford's Law. The results show that NFFS6 SACCO entries closely followed Benford's Law except where 1 was the first digit.

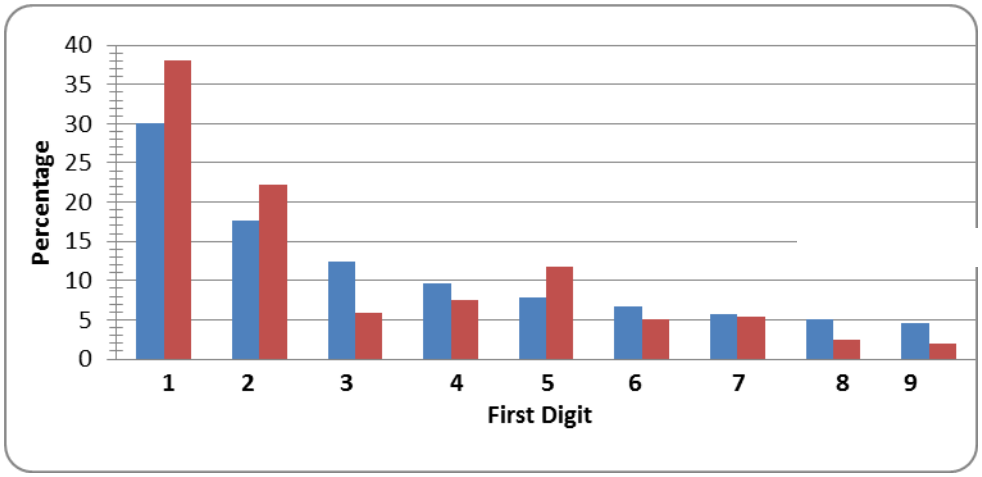


Figure 4. 21: Benford`s Law Vs NFFS7 SACCO

Figure 4.21 shows a comparison of NFFS7 SACCO entries and Benford's Law. The results show that NFFS7 SACCO entries closely followed Benford's Law except where 1, 2and 5 were the first digits.

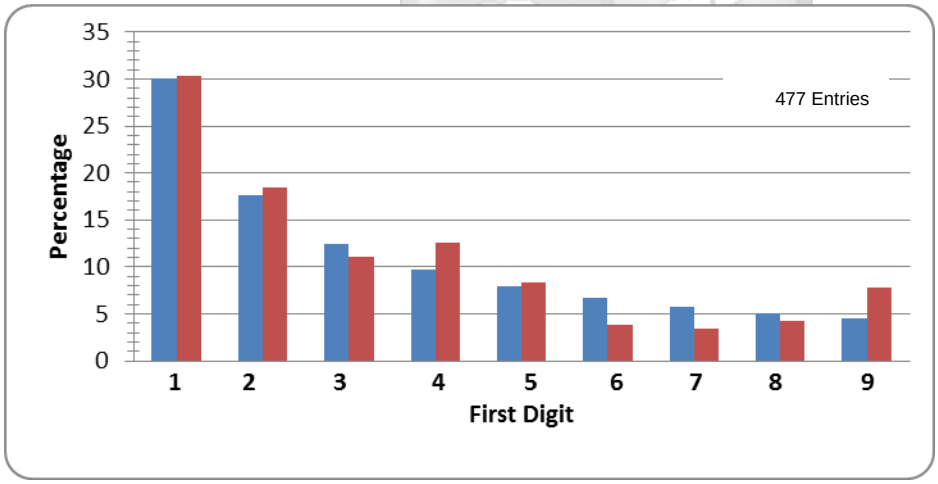


Figure 4. 22: Benford`s Law Vs NFFS8 SACCO

Figure 4.22 shows a comparison of NFFS8 SACCO entries and Benford's Law. The results show that NSFFS8 SACCO entries closely followed Benford's Law except where 4 and 9 were the first digits.

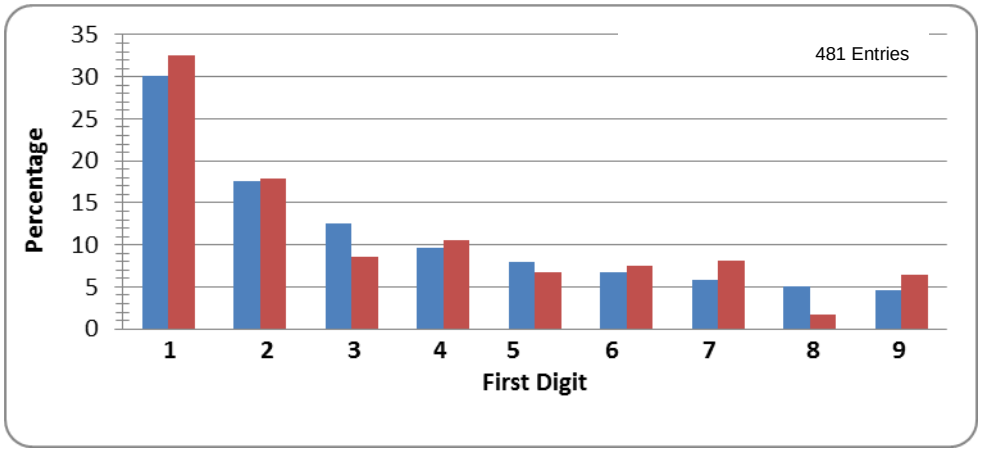


Figure 4. 23: Benford`s Law Vs NFFS9 SACCO

Figure 4.23 shows a comparison of NFFS9 SACCO entries and Benford's Law. The results show that NFFS9 SACCO entries closely followed Benford's Law.

Table 4.13: First Digit Analysis for NFFS10 SACCO

	Observed N-NFFS10	Expected N-Benford's Law	Residual
1	102	101.47	0.53
2	57	59.34	-2.34
3	24	42.104	-18.104
4	47	32.66	14.34
5	35	26.68	8.32
6	23	22.56	0.44
7	15	19.54	-4.54
8	19	17.24	1.76
9	15	15.42	-0.42
Total	337		

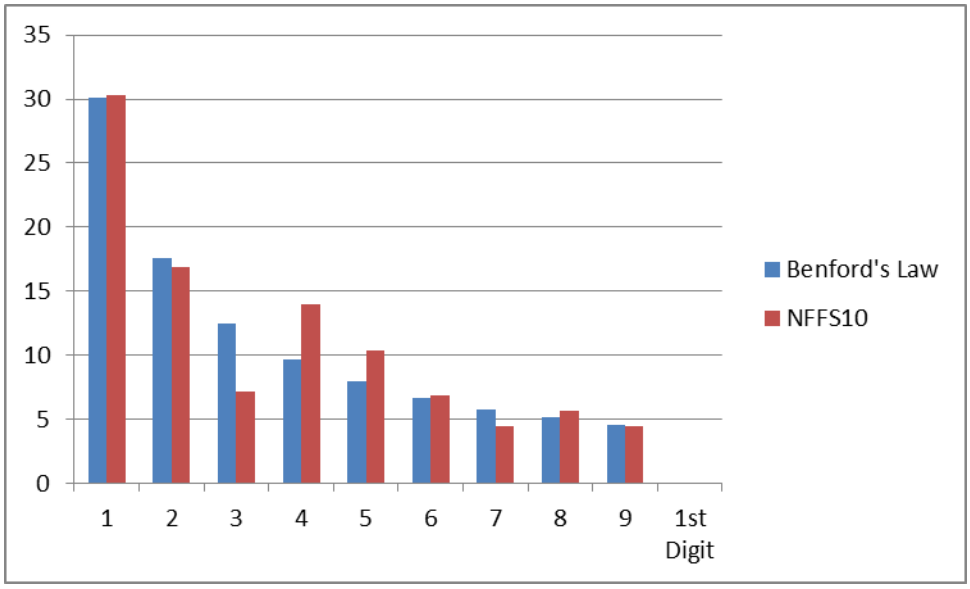


Figure 4. 24:Benford`s Law Vs NFFS10 SACCO

See appendix II-NFFS10

Figure 4.24 shows a comparison of NFSS10 SACCO entries and Benford's Law. The results show that NFFS10 SACCO entries closely followed Benford's Law**.**

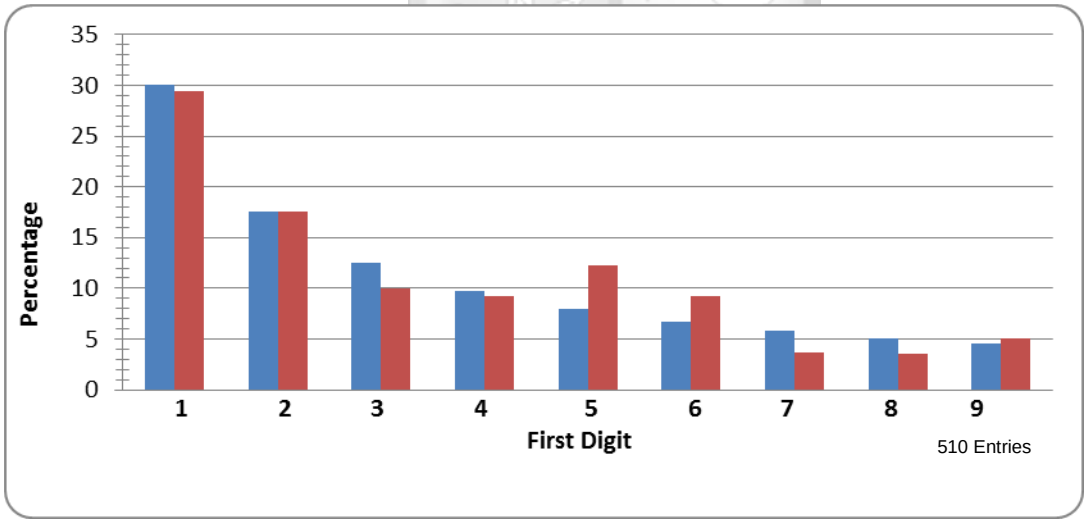


Figure 4. 25: Benford`s Law Vs NFFS11 SACCO

Figure 4.25 shows a comparison of NFFS11 SACCO entries and Benford's Law. The results show that NFFS11 SACCO entries closely followed Benford's Law except where 5 and 6 are the first digits.

Chi-square test was done to determine goodness of fit for this sub-category of data. Data from NFFS8 SACCO was used. The results show that the data set was statistically significant X^2= 27.516, p-value < 0.05. Chi-square test results are presented below.

4.5.3 SACCOs with high number of entries

The entries for SACCOs with high number of entries in the category of SACCOs without fraud demonstrated a similar trend by following Benford's Distribution. This is illustrated by NFFS12 SACCO, NFFS13 SACCO, and NFFS14 SACCO.

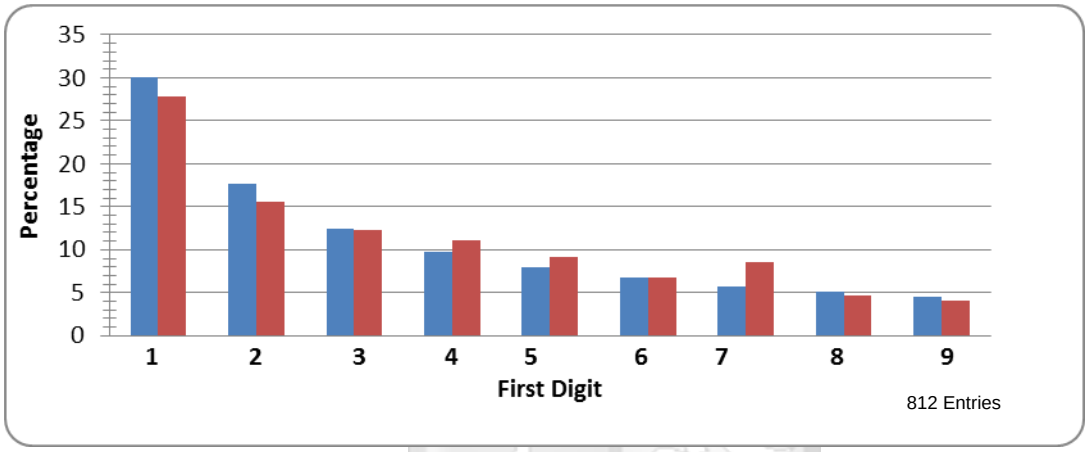


Figure 4. 26: Benford`s Law Vs NFFS12 SACCO

Figure 4.26 shows a comparison of NFFS12 SACCO entries and Benford's Law. The results show that NFFS12 SACCO entries closely followed Benford's Law.

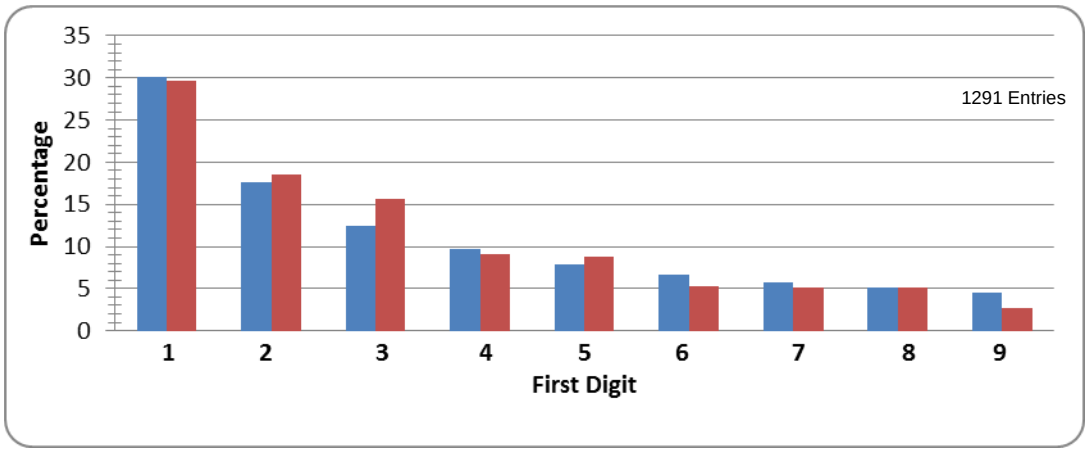


Figure 4. 27: Benford`s Law Vs NFFS13 SACCO

Figure 4.27 shows the results of a comparison between NFFS13 SACCO entries and Benford's Law. According to the results, NSSF13 SACCO entries closely followed Benford's Law.

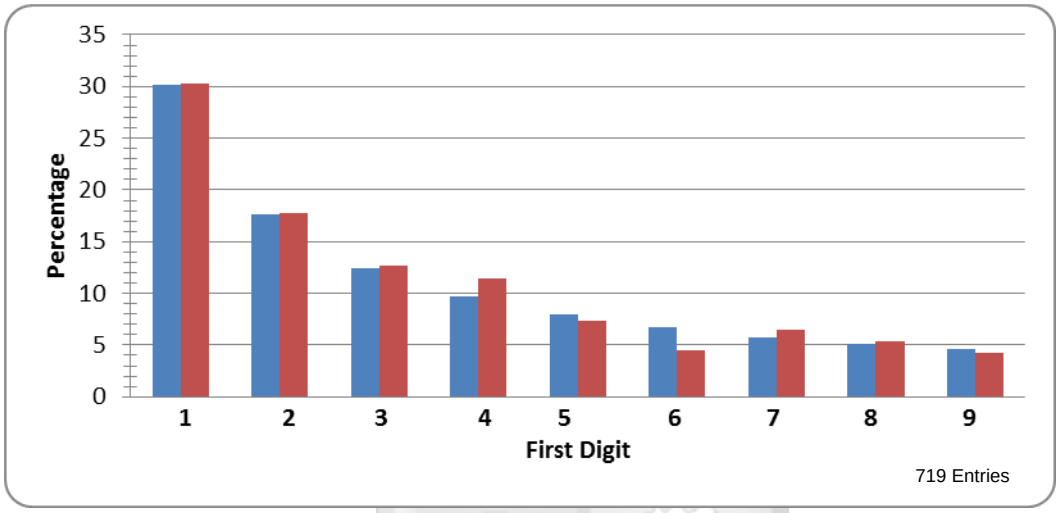


Figure 4. 28: Benford`s Law Vs NFFS14 SACCO

The results of a comparison between NFFS14 SACCO entries and Benford's Law are shown in Figure 4.28. According to the results, NFFS14 SACCO entries closely followed Benford's Law.

Table 4.14: SACCOS without fraud Summary

SACCOS without fraud	P-Value	Chi Square	Decision
NFFS1	0.165	11.707[a]	R
NFFS2	0.016	18.813[a]	A
NFFS3	0	29.235[a]	A
NFFS4	0.811	4.485[a]	R
NFFS5	0	61.830[a]	A
NFFS6	0	30.473[a]	A

NFFS7	0	53.569[a]	A
NFFS8	0.001	27.519[a]	A
NFFS9	0	28.251[a]	A
NFFS10	0.096	13.484[a]	R
NFFS11	0.01	25.738[a]	A
NFFS12	0.023	17.803[a]	A
NFFS13	0.001	26.382[a]	A
NFFS14	0.353	8.872[a]	R

Key

A= Accept hypothesis R= Reject hypothesis

Out of 14 SACCOs that did not have fraud, Benford's Law could accurately predict that there was no fraud in 10 SACCOs, which is 71.42% accurate. Hence a fair test for fraud detection.

CHAPTER FIVE

DISCUSSION

5.1 Introduction

This chapter covers discussions of the findings. It compares the findings of the study with what other researchers have found out in previous studies. It also attempts to explain the observations established in the study.

5.2 Factors Causing Fraud

Factors causing fraud in SACCOs include poor internal control systems, lack of integrity, poor pay of SACCOs' employees and poor management information. Availability of opportunity, poor technology and incompetence of staff are also causes of fraud according to this study's findings. These findings are in agreement with those of Albrecht et al (2004) who observed that many elements come together to form what they referred to as fraud triangle that comprised of pressure to commit fraud, opportunity to commit fraud and inclination to rationalise fraud.

Weak control environment, as noted by Bell and Carcello (2000) and confirmed by this study is a critical factor that causes fraud. Poor internal control systems observed in SACCOs illustrate such a weak control environment in Kenyan SACCOs. Poor pay of SACCOs' employee could be a factor causing fraud in SACCOs. These findings resonate well with those by Watts and Zimmerman (1990) but are contrary to those by Dechow et al. (1996).

5.3 Characteristics of Fraud in SACCOs

Fraud in SACCOs is characterized by dubious entries in financial accounts, cash flow problems, change of lifestyle by employees and non-payment of suppliers. This could be attributed to collusion by employees especially those in authority to fraud SACCOs. These findings are supported by Wells (2008) and KPMG (2009) who noted there are differences in fraud loss amounts that may result from variations in the degree of authority and financial control exercised at different job levels. Wells (2008) and KPMG (2009) argued that managers, top executives and owners have greater access to company funds, assets, and confidential information than lower level employees and therefore within organizations, the hierarchical position may either limit or facilitate certain types of fraud (Holtfreter, 2005).

Another reason why executives and owners may commit fraud is that they have more authority to override existing controls than lower level employees, thus allowing the fraud to grow and go undetected for a longer period of time than other frauds (ACFE, 2008; KPMG, 2009). This makes detection of fraud through observation of its characteristics difficult. Although characteristics such as doubtful financial accounts, cash flow problems, change of lifestyle by employees and non-payment of suppliers maybe a pointer of fraud, if executive and SACCO members are involved it becomes hard to detect it.

5.4 Techniques and approaches of Fraud in SACCOs

The techniques and approaches of fraud detection in Kenyan SACCOs were highlighted as Comparative techniques, Cash flow analysis,Interviews, Review of complaints, whistle blows, tips and hotline registers,Vertical analysis is a technique and horizontal analysis.

5.5 First Digit Analysis for SACCOs with Fraud and without Fraud

The entries for SACCOs with fraud and without fraud partially followed Benford's Distribution as per conventional beliefs. These entries did not show variations in SACCOs with small and high number of entries. The entries for SACCOs with fraud were expected not to follow Benford's distribution while those without fraud were expected to follow Benford's distribution.

These findings are contrary to those of Nigrini and Mittermaier (1997) who showed how auditors can use Benford's Law as an analytical procedure to help discover surprising patterns in transaction activity. This observation that shows Benford's Law applying for both categories of SACCOs puts into focus the reliance on Benford's Law in detection of fraud in accounting data.

This scenario can be explained by existence of other types of fraud that cannot be detected by digital analysis. Tapp and Burg (2001) as they described the role of technology advances in fraud detection processes identified three different fraud contexts that Benford's Law could be used; detecting vendor kickbacks, detecting fictitious vendors, and detecting overstated divisional performance. However, as established there could be frauds that cannot be detected by digital analysis. Such frauds include contract rigging, defective deliveries, or defective shipments. Another possibility is that fraudsters can avoid detection by adhering to Benford's Law knowingly or unknowingly. Benford's Law also has a weakness in that it works best on

large data sets but many frauds are based on just one or two entries. Morrow (2009) and others noticed that Benford's Law is conservative, sometimes extremely so, especially for large data sets.

The observation that first digit analysis partially showed difference between SACCOs with fraud and SACCOs without fraud shows that Benford's distribution as a method of detecting fraud in accounting data is not wholly effective. This finding is contrary to that of Savile (2006) who utilized data taken from companies listed on the Johannesburg Securities Exchange to test the hypothesis that Benford's Law can be used to spot false or fraudulent reporting of accounting data.

The effectiveness of Benford's Law in detection of fraud in accounting data has been questioned recently by Ozer and Babacan (2013). Although Ozera and Babacan (2013) have partial support for use of digital analysis method to determine the fraud and manipulations, they caution on overreliance on this method.

The implication for this observation is that, data sets that comply with Benford's distribution are not necessarily accurate. However, as Ozera and Babacan (2013) are quick to add, the fact that a data set does not comply with Benford's Distribution is enough to be suspicious about that data set.

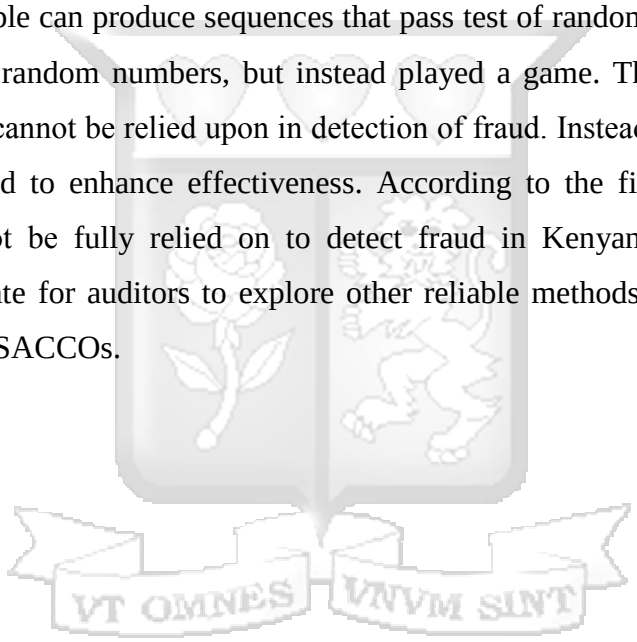
Bhattacharya (2002) could have noticed the weakness of the Benford's Law when he suggested a possible combination of methods that include Benford's Law to be used to help and aid investigative and forensic accountants in tracking and tracing corporate frauds. This study's findings cast doubts on Durtschi et al's (2003) assertion that Benford's Law offers the auditor with a tool that is simple and very effective for the discovery of fraud. It has been established that Benford's Law could be simple but not effective. It is useful but an imperfect fraud catcher.

5.6 Whether Benford's Law can be used to detect fraud in Kenyan SACCOs

Benford's Law can be used to detect fraud in Kenyan SACCOs but this method cannot be used alone. This is because it has been established that first digit analysis method has weaknesses that make it ineffective. It can be therefore useful method in aiding fraud detection but its imperfect fraud catcher.

These results have implications for both the practical and theoretical aspects of Benford's Law. The practical implications are that applications of Benford's Law to search for fraud need to be more nuanced, otherwise they may at best be a waste of time and at worst increase the confidence in data that is in fact invalid. Although previous research suggested that first-digits have a flat distribution in generated data, this appears not to be the case. Understanding what distributions people produce and under what conditions would allow Benford's Law to be more effectively applied to detecting fraud.

Hill's (1995) "Random samples from random distributions theorem" proposed that Benford's Law is what you get when you take random samples from random distributions. Thus people may have a greater ability to act randomly than has been claimed. Rapoport and Budescu (1992) found that people can produce sequences that pass test of randomness when not asked explicitly to generate random numbers, but instead played a game. This help to show that Benford's Law alone cannot be relied upon in detection of fraud. Instead, its important to use more than one method to enhance effectiveness. According to the findings of this study, Benford's Law cannot be fully relied on to detect fraud in Kenyan SACCOs. It would therefore be appropriate for auditors to explore other reliable methods if they are to detect fraud early enough in SACCOs.



CHAPTER SIX

CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This chapter presents conclusions and recommendations of the study. These conclusions as well as recommendations are informed by the study findings.

6.2 Conclusions

The study revealed that there are many factors that causes fraud but could be summarized as those causing pressure to commit fraud, those creating an opportunity to commit fraud and those inclined to rationalizing fraud. Weak control environment, lack of integrity among employees and poor pay of SACCOs' employees are key factors that cause fraud in SACCOs.

Fraud in SACCOs was found to be characterized by well-connected members and executives who are in a position to control and use their authority to conceal fraud. This could be demonstrated by variations in amounts involved where fraud by executives and members is large scale as opposed to that perpetrated by employees. Doubtful financial accounts, cash flow problems, change of lifestyle by employees and non-payment of suppliers are red flags to indicate possibility of fraud in a SACCO but their absence does not mean there is no fraud. This is because as it has been established by this study, some fraud can go undetected for a long period of time. It is therefore advisable to combine many methods of fraud detection to ensure success.

Review of complaints, whistle blows, tips and hotline registers was found to be the most effective fraud detection approach followed by cash flow analysis, Comparative techniques, Vertical analysis, Interviews then horizontal analysis.

This study revealed that reliance on Benford's Law for detection of fraud needs a review to ascertain its effectiveness. This is due to lack of clear variations in a test of a data set with fraud and another that did not have fraud. This shows that Benford's Law reliability cannot be guaranteed.

Benford's Law has inherent weaknesses that could be the reason for its sometime imperfect nature in fraud detection. Some frauds cannot be detected by digital analysis because they are one off. If there are few fraudulent transactions a significant difference will not be triggered even if the total amount is huge. Such fraudulent transaction include contract rigging, defective deliveries, or defective shipments makes it necessary to employ more than one method in an attempt to detect fraud. Reliance on digital analysis alone could give misleading results as established in this study.

The inability of Benford's Law to work well with small data sets makes it an ineffective tool of fraud detection. Benford's Law works best on large data sets but many frauds are based on just one or two entries that could pass undetected by digital analysis.

Although there has been a consensus that Benford's Law is a useful tool in fraud detection, it is important to recognize its weaknesses and use it with other methods that would be in a position to complement it for effectiveness in fraud detection. Overreliance on this method is therefore not appropriate for fraud detection. Data sets that comply with Benford's Law therefore should not be treated as accurate until passed through other fraud detection methods.

6.3 Recommendations

This study recommends that auditors should use Benford's Law in fraud detection.Auditors should be careful when working on small data sets using Benford's Law to detect fraud. This is because Benford's Law works best on large data sets. The auditors should realize that fraud could be perpetrated through one or two entries and this could pass unnoticed in digital analysis. It is therefore recommended that Benford's Law should be an as an exploratory tool at preliminary stage for detecting fraud but not a primary one.

6.3.1 Suggestions for Further Research

This study recommends that further research should be carried out to ascertain whether the other position behave in a similar manner when subjected to two different data sets; with fraud and without fraud. Future research should focus on establishing the reliability of Benford's Law in detection of fraud. Further research should review weaknesses of Benford's Law and come up with other appropriate methods that complement the method.

REFERENCES

Afya SACCO (2005). Afya SACCO Society Limited, Homepage, http://www.afyaSACCO.com, accessed on 27th August 2012

Albrecht, W. S. (2003). Fraud Examination. Mason, Ohio, South-Western.

Albrecht, W. and Wernz, G. (1995). Fraud bringing light to the dark side of business. Burr Ridge IL, Irwin.

Albrecht, W. S., Albrecht, C. C. and Albrecht, C. O. (2004). Fraud and Corporate Executives: Agency, Stewardship and Broken Trust, Journal of Forensic Accounting. Vol. 5 pp. 109-130

Allen, F. and Gale, D. (2001). Comparing Financial Systems, MIT Press, Cambridge, MA, .

Arthur, A. (1995). Pre-emptive fraud investigations and the audit function, The Journal of Applied Accounting Research, Vol. 2, No. II, pp. 21–49.

Association of Certified Fraud Examiners (2010). Report to the Nation on Occupational Fraud and Abuse, Association of Certified Fraud Examiners, Austin, TX,

Association of Certified Fraud Examiners (2012). Report to the Nations on Occupational Fraud and Abuse The Surprising "Benford Law" of Leading Digits July 5, 2011 by Mike DeHaan

Association of Certified Fraud Examiners (2014). Report to the Nation on Occupational Fraud and Abuse, Association of Certified Fraud Examiners, Austin, TX

BBC News (2003). Parmalat boss denies fraud role, BBC News, world edition, December 31, available at: http://news.bbc.co.uk/2/hi/business/3355929.stm, .

Benford, F. (1938). The Law of Anomalous Numbers. In Proceedings of the American Philosophical Society 78, 551-572.

Beresford, D. Katzenbach, N. and Rogers, C. (2003). Report of investigation by the special investigative committee of the Board of Directors of WorldCom, Inc.

Bhattacharya, S. (2002). From Kautilya to Benford – Trends in Forensic and Investigative Accounting. 9th World Congress of Accounting Historians, Deakin University

Bloomberg News (2004). Witness says Cendant execs reviewed fake earnings, Bloomberg News, Los Angeles Times, June 30, .

Bologna, G. J. and Lindquist, R. J. (1995). Fraud auditing and forensic accounting. New York, John Wiley and Sons.

Busta, B. and Weinberg, R. (1998). Using Benford's Law and neural networks as a review procedure. Managerial Auditing Journal 13 (6): 356-366.

Coderre, D. (1999). Computer-Assisted Techniques for Fraud Detection. The CPA Journal (August): 57-59.

Coenen, T. (2014). Three Basic Fraud Types. AllBusiness.com retrieved on 2nd February, 2014 from http://www.allbusiness.com/crime-law-enforcement-corrections/criminal-offenses/6635361-1.html

Commonwealth of Australia (2003). The failure of HIH insurance, April, available at: www.hihroyalcom.gov.au/finalreport/Front%20Matter%2C%20critical%20assessment%20 and%20summary.HTML, .

Conner, D. S. (2003). Social comparison in virtual work environments. Journal of Occupational and Organizational Psychology, 76: 133.

Cressey, D. R. (1973). Other People's Money: A Study in the Social Psychology of Embezzlement. Montclair, Patterson Smith.

Davis, J.H., Schoorman, F.D. and Donaldson, L. (1997). Toward a stewardship theory of management, The Academy of Management Review, Vol. 22, pp. 20-47.

Dixon, J. (2002). Taubman sentenced to one year in prison for Sotheby's price-fixing, Detroit Free Press, April, pp.22.

Dubinsky, B. G. (2001). Legal Times Math Formula Fights Fraud: Benford's Law Plus Technology Can Detect White Collar Crime, Vol. 24

Durtschi, C., Hillison, W. and Pacini, C. (2004). The effective use of Benford's Law to assist in detecting fraud in accounting data. Journal of Forensic Accounting Vol. 5 pp. 17-34.

Fisher, D. (2002). Shell game, Forbes, February 14, .

Gob, R., (2007). Data conformance testing by digital analysis: A critical review and an approach to more appropriate testing. Quality Engineering, 19 (4), 281-297.

Guardian Newspapers (2002). Andersen 'debated dumping Enron account', Guardian Newspapers, May 15, available at: www.buzzle.com/editorials/text5-15-2002-18461.asp, .

Guardian Newspapers (2003). More arrests as Parmalat fraud scandal deepens, Guardian Newspapers, December 31, available at: www.buzzle.com/editorials/12-31-2003-49031.asp, .

Hales, D.N., Sridharan, V., Radhakrishnan, A., Chakravorty, S.S., and Siha, S.M. (2008). Testing the accuracy of employee-reported data: An inexpensive alternative approach to traditional methods. European Journal of Operational Research, 189, 583-589.

Hancox, D.R. (1997). Equity funding: could it happen again? available at: http://home.nycap.rr.com/dhancox/articles.equity.htm, .

Hecht, K. and Murphy, C. (2000). Current computer security threats to American business: A high level review. DIA/FBI/NSA Joint Commission on Technology Protection. Santa

Hill, T. P. (1995a). Base-invariance implies Benford's Law. Proc. Am. Math. Soc. 123, 887-895.

Hill, T. P. (1995b). A statistical derivation of the significant digit law. Statis. Science 10 (4), 354-363.

Hill, T.P. (1995c). The Significant-Digit Phenomenon. American Mathematical Monthly 102 (4): 322-327.

Hill,T.P. (1998). The first digital phenomenon. American Scientist, Vol. 86(4)

Hollinger, R. C. and Clark, J. P. (1983). Theft by employees. Lexington MA, Lexington Books.

Humphrey, C., Turley, W. S. and Moizer, P. (1993). Protecting against detection: The case of auditors and fraud? Accounting, Auditing and Accountability Journal, Vol. 6, No.1, pp. 39–62.

Investopedia, (2014). Corporate Fraud: Definition of 'Corporate Fraud'. Retrieved on 2nd February, 2014 from http://www.investopedia.com/terms/c/corporate-fraud.asp

Krakar, Z. and Zgela, M. (2009). Application of Benford's Law in Payment Systems Auditing, Journal of Information and Organizational Sciences, Vol. 33, (25)

Krambia-Kapardis, M. (2002). A fraud detection model: A must for auditors, Journal of Financial Regulation and Compliance, Vol. 10 (3), pp. 266–278.

Lari, L.R. (2009). The Power of Financial Ratios in Detecting Fraudulent Financial Reporting: The Case of Savings and Credit Co-Operative Societies in Kenya. Unpublished MCOM Thesis, Strathmore University

Ley, E. (1996). On the Peculiar Distribution of the U.S. Stock Indexes' Digits. The American Statistician 50 (4): 311-313.

Lyke, B (2002). Worldcom: The accounting scandal.CRS report for congress.

Lolbert, T (2006). Digital Analysis: Theory and Applications in Auditing. Hungarian Statistical Review, Vol. 84(10)

Lu, F, Boritz, J.E. and Covvey, D. (2006). Adaptive fraud detection using Benford's Law. Lecture Notes in Computer Science 4013, 347-358.

Maney, K. (2000). Baffled by math? Wait 'til I tell you about Benford's Law. The USA Today (October 18): B3.

Ministry of Co-operative Development and Marketing (2008). Homepage-achievements, frequently asked questions (FAQs), http://www.cooperative.go.ke , accessed on 6th March, 2008

Ministry of Co-operative Development and Marketing (2012). Background, http://www.cooperative.go.ke, accessed on 27th August, 2012

Monroe, G. S. and Woodliff, D. R. (1994). Great expectations: Public perceptions of the auditor's role', Australian Accounting Review, Vol. 4, No. 2, pp. 42–53.

Morrow, J. (2010). Benford's Law, families of distributions, and a test basis. URL http://www.johnmorrow.info/projects/benford/benfordMain.pdf, accessed on 10th April, 2013

Mugwe, D. (2012). Inside Harambee Sacco's mega fraud. Business Daily (December 9, 2012). Retrieved from http://www.businessdailyafrica.com/Inside-Harambee-Sacco-mega-fraud/-/539546/1640192/-/1e9i54z/-/index.html

Newcomb, S. (1881). Note on the Frequency of Use of the Different Digits in Natural Numbers American Journal of Mathematics Vol. 4(1) pp. 39-40

Nieschwietz, R. J., J. Joseph J. Schultz, et al. (2000). Empirical Research on External Auditors' Detection of Financial Statement Fraud. Journal of Accounting Literature 19: 190-246.

Nigrini, M. (1999). Adding Value with Digital Analysis. Internal Auditor (February): 21-23.

Nigrini, M. J. and Miller, S. J. (2009). Data diagnostics using second order tests of Benford's Law. Auditing: A Journal of Practice and Theory. Vol. 28(2).

Nigrini, M., and L. Mittermaier. (1997). The Use of Benford's Law as an Aid in Analytical Procedures. Auditing: A Journal of Practice and Theory 16 (2): 52-67.

Nigrini, M.J. (1999). I've got your number. Journal of Accountancy 187(5), 79-83.

Nooraslinda A. A., Rohana O. et al.,(2013) Fraud Detection: Benford's Law vs Beneish Model

Ozera, G. and Babacan, B. (2013). Benford's Law and Digital Analysis: Application on Turkish Banking Sector. Business and Economics Research Journal Vol. 4(1) pp. 29-41

Patsuris, P. (2002). The Corporate Scandal Sheet. Forbes Online retrieved on 2nd February, 2014 from http://www.forbes.com/2002/07/25/accountingtracker.html

Pinkasovitch, A. (2011). Detecting Financial Statement Fraud. Investopedia, accessed online at www.investopedia.com/articles/financial-theory/11/detecting-financial-fraud-asp

Porter, B. A. (1993). An empirical study of the audit expectation-performance gap, Accounting and Business Research, Vol. 24, No. 93, pp. 49–78.

PwC. (2003). Stand and Be Counted. PricewaterhouseCoopers Advertorial Campaign. New York, NY.

PWC.(2007). Economic crime: people, culture and controls. The 4th biennial Global Economic Crime Survey

Reinstein, A. Moehrle, R. and Reynolds-Moehrle, J. (2006). Crime and punishment in the marketplace: Accountants and business executives repeating history, Managerial Auditing Journal, Vol. 21 Iss: 4, pp 420 – 435

Rezaee, Z. (2005). Causes, consequences, and deterrence of financial statement fraud. Critical Perspectives on Accounting, 16(3), 277-298.

Robb,G.(1992) Financial fraud and business morality. White collar crimes in the modern England

Sadgrove, K. (1996). The complete guide to business risk management, Gower: Hampshire.

Saville, A. D (2006). Using Benford's Law to detect data error and fraud: An examination of companies listed on the Johannesburg Stock Exchange. Gordon Institute of Business Science, University of Pretoria

Securities and Exchange Commission (1985), Roundtable on Major Issues, September 5 and 11, 1985, Background Materials, available at: www.sechistorical.org/museum/papers/pdf/SEC_RT_MjIssues_1985_BGMat.pdf, .

Securities and Exchange Commission (2002), Complaint by Securities and Exchange Commission (plaintiff) against Adelphia Communications Corporation, John J. Rigas, Timothy J. Rigas, Michael J. Rigas, James P. Rigas, James R. Brown, and Michael C.

Mulcahey(defendants),available at:
www.sec.gov/litigation/complaints/complrl7627.htm, .

Shah N S.(2011) Fraud Detection:Data Mining & Audit Tools.Bombay chartered accountants

Sharma, A. and Panigrahi, P.K. (2012). A Review of Financial Accounting Fraud Detection based on Data Mining Techniques. International Journal of Computer Applications, Vol. 39 (1) pp. 0975 – 8887

Sorensen, J. E., and Sorensen, T. L. (1980). Detecting management fraud: Some organizational strategies for the independent auditor', in Elliott, R. K. and Willingham, J. J. (eds) 'Management fraud: Detection and deterrence', Petrocceli Books, Princeton, New York.

Sundaram, A. K. and Inkpen, A.C. (2004). The corporate objective revisited, Organization Science, Vol. 15, pp. 350-63.

Sundaramurthy, C., Lewis, M. (2003). Control and collaboration: Paradoxes of Government. Academy of management Review, Vol. 28(3) pp. 397-416.

Sutherland, E. H. (1983). White Collar Crime: The uncut version. New Haven CT, Yale University Press.

Tackett, James A. Wolf, Fran M. and Claypool, Gregory A. (2006). Fraud Specialists On Independent Audits, Journal of Business and Economics Research, Vol. 4(7).

Tapp, D., and Burg, D. (2001). Using Technology to Detect Fraud. Pennsylvania CPA Journal

Taylor, T. (2010). Benford's Law: a useful, but imperfect, fraud-catcher

Tommie W S (2011).Understanding and applying Benford`s Law.ISACA Journal

WallaceW. (2002). Assessing the Quality of Data. Journal of Government Financial Management (Fall): 16-22.

Wang, J. and Yang, J.G.S. (2009). Data Mining Techniques for Auditing Attest Function and Fraud Detection Journal of Forensic and Investigative Accounting Vol. 1(1).

Wang, J., Liao, Y., Tsai, T. & Hung, G. (2006). Technology-based financial frauds in Taiwan: issue and approaches, IEEE Conference on: Systems, Man and Cyberspace Oct (2006) 1120–1124.

Wells, J. T. (2008). Accountancy and white-collar crime, Annals of the American Academy of Political and Social Science, Vol. 525, pp. 83–94.

Wanyama, F.O. (2009). Surviving Liberalization: the cooperative movement in Kenya. Working Paper No. 10. International Labour Organization: Dar el Salaam.

APPENDIX I: QUESTIONNAIRE

Introduction

This questionnaire seeks to collect information regarding factors causing fraud, characteristics of fraud and techniques used to detect fraud in Kenyan SACCOs. Kindly answer the questions objectively by writing or ticking in the spaces provided. Do not indicate your name or that of your SACCO anywhere in the questionnaire. The questionnaire has four sections. Section A seeks demographic information of the respondents while section B C and D seeks information on factors causing fraud, characteristics of fraud and techniques used to detect fraud.

Section A: Demographic Information

1. What is your position in this SACCO?

   IT Auditors [ ]

   Compliance managers [ ]

   External auditors [ ]

   Risk managers [ ]

   Internal auditors [ ]

   Others (specify) ……

2. How long have you worked in this SACCO?

   0-3 years [ ]

   4-7 years [ ]

   8-11 years [ ]

   12 years and above [ ]

Section B: Factors Causing Fraud in SACCOs

3. Have you ever encountered fraud in your day to day work?

   Yes [ ] No [ ]

4. If yes, what are the factors do you think have led to fraud in SACCOs?

   .....

   .....

   .....

5. If no above, what would you attribute to lack of fraud in this SACCO?

.....

.....

.....

6. Have you heard of fraud in other SACCOs?

   Yes [ ] No [ ]

7. If yes, what led to fraud in those SACCOs?

   .....

   .....

   .....

8. If no, why do you think there is no fraud in the other SACCOs?

   .....

   .....

   .....

9. To what extent do you agree with the following statements regarding factors causing fraud in SACCOs?

	Not at all	Little extent	Moderate extent	Great extent	Very great extent
Governance of the SACCO					
Internal controls					
Regulations by authorities					
Targets or pressure to deliver where compensation packages are based on reported earnings					
Desire to raise external capital cheaply					
Other (specify)					

Section C: Characteristics of Fraud in SACCOs

10. How would you recognize fraud in a SACCO?

    .....

    .....

    .....

11. What are the common characteristics of major types of fraud in SACCOs?

    .....

    .....

    .....

12. To what extent do you agree with the following statements in regard to recognizing fraud in SACCOs?

	Not at all	Little extent	Moderate extent	Great extent	Very great extent
Cash flow problems					
Non payment of suppliers					
Dubious entries in financial accounts					
Restructuring of loan facilities					
Change of lifestyle by employees					
Other (specify)					

13. What do you think should be done to prevent fraud in Kenyan SACCOs?

    .....

    .....

    .....

14. What other measures would you recommend should be done to curb fraud in SACCOs?

    .....

    .....

    .....

Section C: Fraud detection techniques/approaches used in Kenyan SACCOs

16. What are the common techniques/approaches used to detect fraud in SACCOs.

.....

.....

.....

17.Do you think the application of these fraud detection methods would improve fraud detection of financial statements in Kenyan SACCOs

Yes [ ]

No [ ]

18.Please indicate the extent to which you agree the following fraud detection techniques in financial statements and their effectiveness on Kenyan Saccos. The scale below will be applicable:

Key 1= Not at all 2 = little extent 3 = Moderate extent 4 = great extent 5 = Very great extent

Fraud detection techniques	1	2	3	4	5
Comparative techniques-Comparison of current period information with similar information from prior periods					
Cash flow analysis- cash flow statement reports how money flows into and out of the company justifiably					
Interviews-People in organisations who have both motive and opportunity are the prime candidates fraudulent misstatement hence interviewed.					
Review of complaints, whistle blows, tips and hotline registers					
Vertical analysis is a technique, analyses the relationships between the items on any one of the financial statements in one reporting period.					
In horizontal analysis, The first period in the analysis is considered the base, and the changes in the subsequent period are computed as a percentage of the base period					
Computation of financial Ratio analysis					

APPENDIX II:EXTRACT OFDATA FROM SACCO FINANCIAL STATEMENTS

1.FFS11

STATISTICAL INFORMATION AS AT 31ST DECEMBER 2010

	31.12.2010	31.12.2009
Members deposits	10,466,919	6,137,472
reserves	447,237.50	383,213.00
Current assets	707,430.00	561,613.00
Current liabilities	35,412	20,200
Turnover	669,972.00	486,612.00

INCOME STATEMENT FOR THE YEAR ENDED 31ST DECEMBER 2010

	31.12.2010	31.12.2009
Revenue-Interest from loans to members	611,822.00	410,223.00
Operating income	58,150.00	76,389.00
Total revenue	669,972.00	486,612.00
Expenditure-admin expences	-574,582.50	-300,407.00
other operating expenses	-31,365.00	4,125.00
Total expenditure	-605,947.50	-304,532.00
Net surplus for the year before tax	64,024.50	182,080.00
Net surplus for the year after tax	64,024.50	182,080.00
Less 20%statutory reserve fund	-12,804.90	-36,416.00
Surplus available for distribution	51,219.60	145,664.00
Surplus to retained earnings	51,219.60	145,664.00

BALANCE SHEET AS AT 31.12.2010

	31.12.2010	31.12.2009
ASSETS-Cash & cash equivalent	684,430.00	538,613.00
Trade & other receivables	23,000.00	23,000.00
Loans to members	10,201,640	5,969,188.00
PPE	40,498.50	10,084.00
Total assets	10,949,568.50	6,540,885.00
Liabilities-Members deposits	10,466,919	6,137,472.00
Trade & other payables	32,200	20,200.00
Insurance fund	3,212.00	0.00
Total liabilities	10,502,331.00	6,157,672.00
Shareholders funds-reserves	447,237.50	383,213.00
Total shareholders funds	447,237.50	383,213.00
Total Members funds & liabilities	10,949,568.50	6,540,885.00

CASHFLOW STATEMENT FOR THE YEAR ENDED 31ST DECEMBER 2010

CASHFLOWS FROM OPERATING ACTIVITIES	
Interest Receipts	611,822.00
Other Operating Income	58,150.00
Payment to Employees & Suppliers	(582,162.00)
	87,810.00
Increase/Decrease in Operating Assets	
Loan to members	(4,232,452.00)
Increase/(Decrease) in Operating Liabilites	
Deposits from members	4,329,447.00
Trade and Other Payables	800.00
Increase in insurance fund	3,212.00
Net Cash from Operating Activities	**188,817.00**
CASHFLOWS FROM INVESTING ACTIVITIES	
Purchase of Property and Equipment	(43,000.00)
Net Cash from Investing Activities	
Net Increase/(Decrease) in Cash & Cash equivalent	145,817.00
Cash & Cash at the beginning of the year	538,613.00
Cash & Cash at the end of the year	684,430.00

NOTES TO THE AUDITED ACCOUNTS FOR THE YEAR ENDED 31ST DECEMBER 2010

Other Operating Income	31.12.2010 Kshs	31.12.2009 Kshs
Entrance fee	48,500.00	-
Sale of loan forms	9,400.00	5,100.00
Passbooks	250.00	
Penalties	-	

		71,289.00
Total	**58,150.00**	**76,389.00**
Administration Expenses		
Audit Fees	10,000.00	10,000.00
Audit Supervision Fees	1,000.00	1,000.00
Audit Recoverable Expenses	200.00	200.00
Depreciation	12,585.00	1,440.00
Salaries and wages	210,250.00	172,000.00
Postage and telephone	11,050.00	1,650.00
Travelling expenses	33,900.00	27,000.00
Printing & Stationery	45,485.00	19,185.00
Repairs and Maintenance	41,327.00	3,389.00
Committee meeting expenses	69,411.00	11,692.00
Insurance	-	14,251.00
Miscellaneous expenses	3,374.00	-
Rent	123,000.00	-
City Council license fee	13,000.00	-
By - laws	-	10,600.00
Training & Education	-	11,000.00
Staff termination allowance	-	17,000.00
Total	574,582.50	300,407.00
Other Operating Expenses		
Bank Charges	31,365.00	4,125.00

PROPERTY PLANT & EQUIPMENT

	Computer	Furniture & Fittings	TOTAL
RATE	30%	12.50%	
COST	KSHS	KSHS	KSHS
01.01.2009	-	10,084.00	10,084.00
Additions	34,000.00	9,000.00	43,000.00
30.12.2010			

	34,000.00	19,084.00	53,084.00
ACCUMULATED DEPRECIATION			
01.01.2010	-	3,086.00	3,086.00
For the period	10,200.00	2,385.50	12,585.50
31.12.2010	10,200.00	2,385.00	12,585.00
NET BOOK VALUE			
31.12.2010	23,800.00	16,698.50	4,049.50
31.12.2009	-	10,084.00	10,084.00

CASH AND CASH EQUIVALENT		
Cooperative bank current a/c - reconciled	428,006.00	418,442.00
Cash in hand (Unverified)	6,424.00	120,171.00
Mpesa Float	250,000.00	-
Total	684,430.00	538,613.00
TRADE ND OTHER RECEIVABLES		
Rent Deposit	23,000.00	23,000.00
TRADE AND OTHER PAYABLES		
Audit Fees	11,200.00	20,200.00
Rent Accrued	21,000.00	-
	32,200.00	20,200.00
INSURANCE FUND		
Balance b/f	-	-
Receipts for the year	62,799.00	14,500.00
Insurance Paid	59,587.00	14,500.00
Balance c/d	3,212.00	-
RESERVES		
Entrance fee	-	84,750.00
Statutory Resere	72,496.90	59,692.00
Retained earnings		

	374,740.60	238,771.00
Total	447,237.50	383,213.00

	31.12.2010 (KSHS)	31.12.2009 (KSHS)
MEMBERS DEPOSITS		
BAL B/F	6,137,472.00	3,384,716.00
Refunds during the year	(966,146.00)	(472,100.00)
Receipts during the year	5,295,593.00	3,224,856.00
BAL C/D	10,466,919.00	6,137,472.00
LOANS-Bal b/f	5,969,188.00	3,229,832
Granted during the year	8,096,746.00	3,946,023
Repayments during the year	-3,864,294.00	-1,206,667.00
Bal c/d	10,201,640.00	5,969,188.00
As per MPA	7,658,299.00	5,969,188.00
Difference	2,543,341	0.00

STATEMENT OF CHANGES IN EQUITY AS AT 31ST DECEMBER 2010

	Entarance fees	Retained earnings	Statutory reserves	Total Equity
Bal as at 01/01/2009	43,750	93,107.00	23,276.00	160,133.00
Surplus for the year	0	182,080.00	0	182,080.00
Transfer to statutory reserve		-36,416.00	36,416.00	0
Additions/contributions	41,000	0.00	0	41,000
Bal as at 31/12/2009	84,750.00	238,771.00	59,692.00	383,213.00
As at 01/01/2010	84,750.00	238,771.00	59,692.00	383,213.00
Adjustment in accountinh policies	(84,750.00)	84,750.00		0
Surplus for the year		64,024.50		64,024.50
Transfer to statutory reserve		-12,804.90	12,804.90	0
Bal as at 31st Dec 2010		374,740.60	72,496.90	447,237.50

2.SACCO FFS012

STATISTICAL INFORMATION FOR THE YEAR ENDED 30/09/2009

	30/09/2009	30/09/2008
Fully and partly paid up shares	528,737.00	525,837.00
Entrance fees	0	44,833.00
Statutory reserve fund	246,987.65	246,987.65
General reserve fund	7,207,468.65	7,207,468.65
Revenue reserves	-1,540,288.15	-1,529,357.05
Current assets	6,416,793.70	4,556,361.05
Current liabilities	7,412,947.55	6,119,751.80
Working capital	-996,153.85	-1,563,390.75
Turnover	1,363,772.25	772,178.80

BALANCE SHEET AS AT 30/09/2009

	30/09/2009	30/09/2008
Fully and partly paid up shares	528,737.00	525,837.00
Entrance fees	0	44,833.00
Statutory reserve fund	246,987.65	246,987.65
General reserve fund	7,207,468.65	7,207,468.65
Revenue reserves	-1,540,288.15	-1,529,357.05
	6,442,905.15	6,495,769.25
Fixed assets-schedule A	7,234,619.00	7,854,720.00
Fixed assets-schedule B	204,440.00	204,440.00
	7,439,059.00	8,059,160.00
Current assets-Loans to members	0.00	111,824.40
Farm inputs loans to members	484,380.00	0.00
CAPS	454,569.60	526,293.50
CODF Loans to members	3,052,304.65	2,199,500.00
Stock of processing materials	0.00	8,754.00
Stock of processing seedlings	275,400	275,400.00
KPCU LTD	1,401,533.80	0.00
Debtors-non members	26,741.65	129,161.50
Debtors- members	30,938.50	106,691.30
Staff salaries advance	14,144.85	15,088.15
Cash and bank balances	676,780.65	1,183,648.20
Total current assets	6,416,793.70	4,556,361.06
Current liabilities		
Members payment due-coffee	46,939.00	26,560.00
Members payment due-dairy	823,969.25	48,479.00
Salaries and wages	1,076.00	53,648.00
NSSF	72,944.00	101,521.00
Equity bank loan	101,639.65	1,054,498.80
Loans/cherry advance	145,501.20	2,578,375.00
CODF Loan	5,239,865.00	2,578,375.00

COOP Bank loan	0.00	915,880.00
COOP Bank loan vehicle loan	973,553.45	1,333,440.00
Audit fees	7,460.00	7,350.00
	7,412,947.55	6,119,751.80
Working capital	-996,153.85	-1,563,390.75
Net assets	6,442,905.15	6,495,769.25

PROFIT AND LOSS ACCOUNT	30/09/2009	30/09/2008
Income-coffee activity contribution	1843367.8	601700.1
Nursery activity activity contribution	-30670	72846
Transport activity contribution	30294.75	-11626.5
Dairy activity contribution	-507317.1	106089.2
Entrance fees	3000	3170
Rebates from bank	791	0
sales of water	24000	0
Interest on savings a/c	205.8	0
sundry income	100	0
Gross income	1363772.25	
EXPENDITURE-Committee expences		
Committee education	14307	0
Sitting allowance	88045	81,525.00
Travelling & subsistence	157549	104530
Staff expences		
Education	3800	1200
salaries	113856	102714
overtime	20943	47869
House allowance	12000	12000
Travelling & subsistence	12100	8020
	162699	171803
Financials		
Bank charges	52665.45	97306.15
legal fees	25600	63800
bank charges	173875.1	26633.45
water & elect.	5233.3	1472
security	1441	8178
	258814.85	197389.6
Provisions-Depreciation	634081	318,886.00
Audit fees	6600	6500
supervision fees	660	650
recoverable expences	200	200
	641541	326236
others-Repairs & maintainance	60	1540

NSSF	2400	2400
Members entertainment	35946	812
Members education	0	7400
printing & stationery	19429	5427
postage & telephone	20005	300
book keeping expences	7000	18,216.00
Chemicals & fertilizers	1060	6,700.00
Donations	8000	3000
Sundry expenses	130	1000
Rent & rates	2550	0
	96580.5	46795
Total expenses	1419536.35	928,278.00
Profit/loss	**-55,764.10**	**-156,099.80**

CASHFLOW STATEMENT AS AT 30/09/09

	30/09/2009	30/09/2008
Cash flow from operating activities		
Net surplus before taxation	-55,764.10	-156099.8
add:depreciation	634,081.00	318,886.00
add:provision for audit fees	7,460.00	7,350.00
	585,776.90	170136.2
ANALYSIS OF CHANGE IN W/C		
INCREASE/DECREASE in debtors	-1,222,417.85	78,853.45
	8,754.00	-108,754.00
	1,293,085.75	3808928.5
Net change in WC	**79,421.90**	**3779027.95**
CASHFLOW FROM INVESTING ACTIVITIES		
Purchase/disposal of investment	0	6530
Purchase/disposal of fixed assets	14000	1436160
Loans advanced to members	-1153616.35	-2198913.8
Loan repayment	0	0
Cash flow from investing activities	**-1167616.35**	**-3641603.8**
cash from financing activities		
Share contribution/refunds	2,900.00	850
Sinking fund contribution/refunds	0	0
Net cash from financing activities	**2,900**	**850**
cash from financing/investing activities	-1164716.35	-3640753.8
Net change in cash&cash equivalent	-506,867.55	301,060.35

FIXED ASSET SCHEDULE	NBV	ADD/LESS	TOTAL	DEP B/F	DEP	TOTAL DEP	NBV 30/09/09
LAND	3650000	0	3650000	0	0		3650000
BUILDINGS-PERMANENT	1489125	0	1489125	552180.2	74,456	626636.2	1414669
BUILDINGS-SEMI PERMANENT	431	0	431	22058.5	431	22489	0
PLANT&MACHINERY	512000	0	512000	365576.35	102400	467976.4	409600
POSHO MILL	140800	0	140800	494392	28160	522552	112640
FURNITURE	12677	0	12677	29816	1267	31083	11410
OFFICE EQUIPMENT	900	0	900	3870	90	3960	810
CALCULATOR	0	1200	1200	0	180	180	1020
WEIGHING SCALE	8300	1500		4710	1225	5935	8575
SPRAY PUMPS	1416	0	1416	4734	177	4911	1239
DAIRY EQUIPMENT	28829	0	28829	10631	4324	14955	24505
LACTOMETER	504	0	504	56	50	106	454
PLASTIC CONTAINERS	1350	0	1350	150	135	285	1215
DRYING TABLES	1101	0	1101	42690	275	42965	826
MOTOR VEHICLE	1431600	0	1431600	0	357900	357900	1073700
LOOSE TOOLS	49	350	49	15861.2	199	16060	200
PRESSURE LAMPS	226	0	226	332	22	354	204
KITCHEN WARE	925	0	925	1632	92	1724	833
CELL PHONE	14972	10950	14972	26752	3888	30640	22034
WHEEL BARROWS	1240	0	1240	1990	124	2114	1116
BOREHOLE PIPING SYSTEM	742	0	742	33777	148	33925	594
WATER PIPING SYSTEM	111502	0	111502	379,077.00	13937	393014	97565
WATER TANKS	445500	0	445500	104,500.00	44550	149050	400950
ADDING MACHINE	511	0	511	2543	51	2594	460

3.SACCO NFFS03

STATISTICAL INFORMATION FOR THE YEAR ENDED 31.12.2011

	31.12.2011	31.12.2010
Share capital	150,000	150000
Statutory Reserve	62,450	51422
Appropriation account	249,801.40	205691
Members deposits	8,350,129.00	5748084
Loans to members	8,186,814	4462620
Shareholders funds	537,236.30	482098.75
Total assets	9,752,295	6667782.75
Total liabilities	9,215,059	6185684
Total revenue	1,080,338	560329.65

INCOME STATEMENT FOR THE YEAR ENDED 31.12.2011

	31.12.2011	31.12.2010
Interest on members loans	1076438.35	557202
Entrance fees	3900	1500
Sundry income-donations	0	1627.65
Total revenue	1080338.35	560329.65
Interest expenses	-800000	-400000
Net interest income	280338.35	160329.65
Administrative expenses	-95820	-67605
Financial expenses	-106380.8	-21180
Other expenses	-23000	0
Total Expenditure	(225200.8.)	-88785
Net operating surplus	55137.55	71544.65
less:Prov.for tax	0	0
less:20% statutory reserve	-11,028.00	14308.9
Retained surplus for the year	44109.55	57235.75

Balance Sheet as at 31.12.2011	31.12.2011	31.12.2010
ASSETS		
Cash and cash equivalent	1055704.3	1372867.75
Loans to members	8186814	4462620
Debtors	286277	608795
Investments	223500	223500
Total assets	9752295.3	6667782.75
LIABILITIES		
Provision for audit fee	5700	5700
Creditors&accruals	35200	31900
Interest on members deposits	824030	400000
Total liabilities	8350129	5748084
	9215059	6185684
Shareholders funds		
Share capital	150000	150000
General reserve	74984	74984
Statutory reserve	62450	51422.9
Appropriation account	249801.4	205691.85
Total shareholders funds	537236.3	482098.75
Total liability & Members funds	9752295.3	6667782.75

Cashflow statements as at 31.12.2011

Cashflow from operating activities		
Interest on members loans	1076438.35	557202
Entrance fees	3900	1500
Sundry income	0	1627.65
Interest expense	-375970	0
Payment for expenses	-219500.8	-83085
	484867.55	477244.65
Increase/Decrease in operating assets		
Loans advanced to members	(3,724,194.00)	(2,118,534.00)
Increase/Decrease in Receivables & Prepayments	322,518.00	(238,335.00)
	(3,401,676.00)	(2,356,869.00)
Increase/Decrease in Operating liabilities		
Members Deposits Contributions	2,602,045.00	2,521,384.00
Audit and Supervisory fees paid	(5,700.00)	(5,700.00)
Increase/Decreasein creditors	3,300.00	31,900.00
	2,599,645.00	2,547,584.00
Net cashflow from Operating Activities (A+B+C) before Income tax	(317,163.45)	667,959.65
Income Income tax	-	-
Net cashflow from Operating Activities	**(317,163.45)**	**667,959.65**
Cashflow from Investing activities		
Purchase of Investments	-	-
Cashflow from Investing activities	-	-
Cashflow from Financing Activities	-	-
Share Contribution	-	-
Net cashflow from financing activities	-	-
Net (decrease)/Increase in cash & cash equipment	**(317,163.45)**	**667,959.65**
Cash & cash equivalent at the beginning of the year	1,372,867.75	704,908.10
Cash & cash equivalents at the end of the year	**1,055,704.30**	**1,372,867.75**

NOTES AND OBSERVATION OF THE ACCOUNTS FOR THE YEAR ENDED 31.12.2011

	2011	2010
	Kshs	Kshs
Administration expenses		
Committee sitting allow.	10,000.00	16,525.00
Committee seminars	-	2,000.00
AGM expenses	66,000.00	-
Printing & stationery	3,120.00	2,380.00
Contribution to KUSCCO	8,000.00	8,000.00
KUSCCO Subscription	3,000.00	3,000.00
Audit fee	5,000.00	5,000.00
Supervision fee	500.00	500.00
Recoverable expenses	200.00	200.00
	95,820.00	37,605.00
Financial expenses		
Bank charges	31730.8	21180
Insurance	74650	0
Total	106380.8	21180
Other expenses		
Book keeping expenses	20000	30000
Seminar expenses	3000	0
Total	23000	30000
Cash & Cash equivalents		
coop bank current a/c	859544	1170908.35
Bank savings a/c	196159.4	201959.4
	1055704	1372867.75
Loans to members		
Balance as per control a/c	8186814	4462620
Balance as per members schedule	8186814	4462620
Differences	0	0
Debtors & Prepayments		
Malindi salt ltd	1500	0
Polly propelin bags	75490	0
Mombasa polythene bags	98014	0
Kitale industries	111273	0
Totals	286277	0

Investments		
KUSCCO shares	11000	11000
Safaricom shares	212500	212500
	223500	223500
Creditors & accruals		
Mombasa maize millers	6000	0
Accruals	23000	0
Creditors	6200	0
Total	35200	31900
Interest on members deposits		
Balance b/f	24030	
Provision for the year	800000	400000
Total	824030	400000
Members deposits		
Balance as per control a/c	8350129	5748084
Bal.as per members scheme	8350129	5748084
Differences	0	0
Share capital		
Balance as per control a/c	150000	150000
Bal.as per members scheme	150000	150000
	0	0
Statutory reserve fund		
Bal b/f	51422.9	37114
Prov.for the year	11028	14308.9
	62450	51422.9
Appropriation account		
Bal b/f	205691.85	148456.1
Retained earnings for the year	44109.55	57235.75
Total	249801.4	205691.85

STATEMENT OF CHANGES IN EQUITY

	SHARE CAPITAL	STATUTORY RESERVES	GENERAL RESERVE	APPROPRIATION A/C	TOTAL
Bal as 01.01.2010	150,000	37114	74984	148456.1	410554.1
Restated bal	150000	37114	74984	148456.1	410554.1
Surplus/deficit for the year	0	0	0	57235.75	57235.75
Transfer to reserve	0	14308.9	0	0	14308.9
Bal as at 31.12.2011	150000	51422.9	74984	205691.85	482098.8

4.SACCO NFFS10

STATISTICAL INFORMATION

FINANCIAL	31.12.2011	31.12.2010
Total assets	67301442	55209610
members deposits	52156907	40458225
External borrowing	0	0
Loans & advances to members	47767954	35957428
investments	1506761	1328176
Core capital	2118553	1795333
share capital	977100	730100
institutional capital	1141453	1065233
Total revenue	18869985	7143628
Total interest income	6133952	4702893
Total expenses	-18707583	-6980554

Statement of comprehensive income as at 31.12.2011

Interest from loans granted to members	6073970	4646897
other interest income	59982	55996
Total interest income	6133952	4702893
Interest expenses	-4164850	-2870600
Net interest income	1969102	18322933
other operating income	12736033	2440735
Net operating income	14705135	4273028
Expenditure-financial	273245	265106
Personal expenses	302400	0
Administration expenses	478181	484763
Governance expenses	699778	395085
other operating expenses	12789129	2965000
	14542733	4109954
Net oprating surplus	**162402**	**163075**
Income tax expese	36183	16624
Net surplus for the year	126219	146451
20% transfer to statutory reserve	-25244	-29290
Surplus available for distribution	100976	117161

STATEMENT OF FINANCIAL POSITION 31.12.2011

ASSETS	31.12.2011	31.12.2010
Cash & cash equivalents	4785030	2413932
Prepayments	6748818	7065034
loans	47767954	35957428

financial assets	1506761	1328176
PPE	6492879	8445040
Total assets	67301442	55209610
Liabilities-Members dposits	52156907	40458225
current income tax	52806	16624
interest payable	4613763	3252809
creditors & payables	859418	186620
Interest bearing liabilities	7499995	9499999
	65182889	53414277
Equity-Share capital	977100	730100
Reserves	1141453	1065233
Total equity	2118553	1795333
Total liabilities	67301442	55209610

CASHFLOW STATEMENT AS AT 31.12.2011	31.12.2011	31.12.2010
Cash flow from operating activities		
Interest receipts	6073970	4646897
interest payments	0	0
Payments to suppliers/employees	-14542733	-4109954
	-8468763	536944
Adjustments for:Prior year	0	-44671
Provision for loan loss	143735	180691
Depreciation charge	2000162	560359
total	-6324866	1233232
Increase/decrease in operating liabilities		
Loans granted to members	-57055950	-33171200
loan repayments	45101689	23908193
prepayments&other receivables	316216	-3970384
	-11638045	-13233991
Deposits from members	14844302	12031900
deposits refunded	-3145620	-571199
Decrease in sundry payables	672798	114820
	12371480	11575521
net cash flow from operating activies		
income tax paid	0	-14418
	-5591431	-439566
Purchase/sale of investments	-178585	-170639
purchase of PPE	-48000	-9005400
Interest received	59982	55996
Dividends received	181236	110825

	14632	-9009218
Cash flow from financing activities		
Share capitalcontributions	247000	241000
Procceds from longterm borrowings	0	10000000
Repayment of longterm borrowings	-2000004	-500001
Investment project receipts	1254219 7	2310660
Members entrance fees	12600	19250
Dividends and interest paid	-2853896	-1919737
Net cash from financing activities	7962529	1141954
Net(decrease)/incraese	2371098	702388
Cash&cash equivalents b/f	2413932	1711544
Cash&cash equivalents for the year	**4785030**	**2413932**

Statement of changes in equity as at 31.12.2011

	share capital	statutory reserves	Retained earnings	Total
Bal b/f	489100	227200	786254	1502554
Prior period adjustment	0	0	-44671	-44671
As restated changes in equity	489100	227200	741583	1457883
surplus for the year	0	0	146451	146451
total	489100	227200	888033	1604333
shares issued for cash	241000	0	0	241000
Committee honoraria	0	0	-50000	-50000
Transfer to statutory reserve	0	29290	29290	0
As at 31.12.2010	730100	256490	808743	1795333
Suplus for the year	0	0	126219	126219
	730100	256490	934962	1921553
Additional reserves	247000	0	0	0
Committee honoraria	0	0	-50000	-50000
Transfer to statutory reserve	0	25244	**-25244**	0
As at 31.12.2011	**977100**	**281734**	**859719**	**2118553**

NOTES:

Administration expenses		
audit fee	20000	108000
membership subscription	11000	11000
insurance-loan risk	261460	194782
insurance-GPA premiums	23868	23868
Printing & stationery	13000	28300
advert.	48800	21000
pr	10000	15000
postage	0	500

Entertainments	0	9000
Audit disbursement	11000	9000
Auditors remmunneration	55000	45000
VAT	8800	7200
Supervision	5700	4700
Depreciation charge	9553	7413
	478181	484763

income tax		
current tax	36183	16624
Defferred tax	0	0
	36183	16624

Motor vehicle operating expenses		
salaries	750032	193800
staff travel	412500	150340
drivers uniform	0	22200
bank charges	0	3650
interest on bank loan	1095046	290473
loan application	0	106000
advance tax	13500	16200
motor vehicle insurance	870153	217830
repairs-general	809950	75284
repairs-tubes & tires	617250	0
fuels & oils	5852759	1274597
investment committee allowance	0	61680
parking & security	96520	0
offloading fees	137500	0
Breakdown towing expenses	53000	0
Miscellenious	90310	0
Provision for depreciation	1990609	552946
	12789129	2965000

Interest income	2011	2010
Interest from loans granted to members	4685760	3799057
Interest from short advances to members	1388210	847840
	6073970	4,646,897

Other Interest income		
Interest from bank deposits	12,982	796
Interest from KUSCCO savings	47000	55200
	59,982	55996
Total interest income	6133952	4702893

Interest expense		
Interest on members deposits-provision	4164850	2870600
Interest on loans and overdrafts	0	0
Total interest expense	4164850	2870600
Other operating income		
Dividend income from investments	181236	110825
Members entrance fees	12600	19250
Other income from operations	12542197	2310660
	12736033	2440735
EXPENSES		
Financial expenses		
Bank charges	127056	82015
KUSCCO charges	2454	2400
Loan loss w/o	143735	180,691
	273,245	265,106
Personnel expenses-sacco		
Salaries & wages	300,000	0
Staff benefits	2,400	0
Staff bonus	0	0
	302,400	0
Governance Expenses		
AGM expenses	214010	145195
Committee education	35030	25000
Committee sitting allowance	147945	88095
Committee travelling allowance	35880	5900
Corporate social responsibility	55000	40000
Members education	211913	90895
	699778	395085

PPE	M/Vehicle	Container office	computer	Equipments	Total
Cost as at 01.01.2010	0	0	0	0	0
Additions/(Disposals)	8847150	118450	0	39800	9005400
	8847150	118450	0	39800	9005400
Depreciation-as at 01.01.2010	0	0	0	0	0
Charge for the year	552,947	6169	0	1244	560,360
	552,947	6169	0	1244	560360
Written down value-31.12.2010	8,294,203	112,281	0	38,556	8,445,040
Additions/(Disposals) as at 01.01.2011	8,847,150	118,450	0	39,800	9,005,400
	0	0	48,000	0	48,000
	8,847,150	118,450	48,000	39,800	9,053,400
Depreciation-as at 01.01.2011	552,947	6,169	0	1,244	560,360

Charge for the year	1,990,609	5,848	2500	1,205	2,000,162
	2,543,556	12,017	2500	2,449	2,560,521
Written down value-31.12.2011	6,303,594	106,433	45500	37,351	6,492,879
	8,294,203	112,281	0	38,556	8,445,040