International Journal of Auditing and Accounting Studies
ISSN: 2582-3272 • Volume 5; Number 2; 2023 : pp. 119-163
https://DOI: 10.47509/IJAAS.2023.v05i02.01

ARF INDIA
Academic Open Access Publishing
www.arfjournals.com

APPLICATION OF BENFORD'S LAW AND THE DETECTION OF ACCOUNTING DATA FRAUD IN NIGERIA

Etim Osim Etim*[1], Emmanuel E. Daferighe[1], Augustine Brenden Inyang and Michael Esua Ekikor[3]

[1]*Department of Accounting, Faculty of Business Administration, University of Uyo, Nigeria*
**(Corresponding author. Email: etimosimetim@uyo.edu.ng)*
[2]*Faculty of Management and Social Science (MASS), Topfaith University Mkpatak, Nigeria*
[3]*Department of Accountancy, Brainfill Polytechnic, Ikot Ekpene, Nigeria*

Article History: *Received: 27 December 2022; Revised: 26 January 2023; Accepted: 15 February, 2023; Published: 10 July 2023*

Abstract: This study employs empirical data to examine how Benford's law can be used to identify accounting data fraud in Nigeria. There is a need for an extra tool in the identification of accounting data fraud due to the alarmingly high level of skill of those who commit accounting data fraud, which is problematic for businesses and others who rely on financial reporting. The goals of this study were to examine the applicability of Benford's law to Nigerian accounting data, assess how well accounting data complied with Benford's law, and assess the possible efficacy of Benford's law in identifying accounting data fraud in the Nigerian context. Data were taken from Cadbury Nig. Plcannual's reports for the previous 15 years. Benford's digits test was used to analyse the data, and the Z-Statistics and Chi-Square (x^2) statistics were used to evaluate the hypotheses. Findings showed that data from errant years failed the conformance test with a 2 value more than the threshold value of 15.51, indicating anomalies, at 36.814 instead of 15.51. The conformance test was passed by the years' data with no inaccuracies thanks to two values falling within the permitted range of 15.51. This demonstrated the usefulness of Benford's Law in identifying accounting data fraud. Therefore, it is advised that it be used in conjunction with other audit approaches to increase audit effectiveness.

Keywords: Benford's Law, Data Fraud, Detection, Audit Effectiveness.

1. INTRODUCTION

Even in a society with perfect accounting systems and impenetrable auditing procedures, fraud and data errors still occur because of human behaviour (Saville, 2006). Today's financial crimes are out of control, and the development

To cite this paper:
Etim Osim Etim, Emmanuel E. Daferighe, Augustine Brenden Inyang & Michael Esua Ekikor (2023). Application of Benford's Law and the Detection of Accounting Data Fraud in Nigeria. *International Journal of Auditing and Accounting Studies*. 5(2), 119-163. *https://DOI: 10.47509/IJAAS.2023.v05i02.01*

of computer software and internet tools has made them even more prevalent. Additionally, these crimes are made much easier to perform while also being harder to identify or minimise (Izedonmi & Ibadin, 2012).

Auditors, shareholders, financial analysts, investment managers, private investors, and other users of publicly published accounting data, such as the revenue services, must therefore be on the lookout for dishonest accounting practises if they are interested in the accuracy of the data. In light of the foregoing, several initiatives are being undertaken to raise accounting standards and auditing procedures. However, the rate of development is sluggish, and the results are incomplete (Saville, 2006). Traditional auditing and investigative methods are inefficient and inadequate at identifying and preventing the numerous forms of fraud that businesses across the world face due to the widespread use of fraud in modern organisations (Onuorah & Appah, 2012). The profession is now searching for analytical tools and audit techniques to find fraud as a result of recent audit failures. Fortunately, at this point, a powerful but little-known mathematical law emerges as a potentially useful tool for uncovering fraudulent activity from a variety of information sets, including accounting data.

Inadvertently developing what is now known as Benford's law, eccentric engineer Frank Benford (1883–1948), who was fascinated in mathematics (particularly numerical patterns), suggested a technique to arrest many of these thieves (Benford, 1938). The use of the law to identify data fraud and inaccuracy, notably in the case of accounting data, is significant in a variety of international contexts. The frequency distribution of the first digits in the numerical data of many real-world collections is governed by Benford's law, a phenomenological law. Inadvertently developing what is now known as Benford's law, eccentric engineer Frank Benford (1883–1948), who was fascinated in mathematics (particularly numerical patterns), suggested a technique to arrest many of these thieves (Benford, 1938). The use of the law to identify data fraud and inaccuracy, notably in the case of accounting data, is significant in a variety of international contexts. The frequency distribution of the first digits in the numerical data of many real-world collections is governed by Benford's law, a phenomenological law. As a result, Benford's law can be thought of as a genuine natural signature that cannot be manually duplicated (Kumar & Bhattacharya, 2003). Accounting numbers typically follow this mathematical law, and because the result is so unexpected, information manipulators frequently disregard the rule. With this information, it is now easy to spot accounting data that has been presented incorrectly or fraudulently.

In the past half century, over 150 articles have been published about Benford's law, a bizarre law based on the number of times a particular digit occurs in a particular position in numbers (Nigrini, 1999). In the past 20 years, a subset of these articles has promoted the use of this law as a simple, effective way for auditors to not only identify operational discrepancies but also uncover fraud in accounting numbers.

Despite this promise, it is surprising to learn that while practitioners have employed Benford's Law in the international context, little to no effort has been made to publish research on the effectiveness of Benford's Law in detecting accounting data mistakes or fraud in a Nigerian scenario. This research project is being carried out in the context of the aforementioned.

1.1. Statement of the Problem

Financial reporting fraud has a serious negative impact on the economy of any country as well as the victim organizations. Financial loss and damage to the organization's reputation are some of its impacts (Burnaby, Howe, & Muehlmann, 2011). The prevalence of accounting data fraud is rising, and it has recently played a major role in several financial scandals. This reality poses challenging issues for management and auditors, as does the growing complexity of fraudsters. It is impossible to overstate the negative economic implications of these data issues because they are regarded as tangible. The Cadbury Nigeria Plc incident has continued to serve as a benchmark for deceptive financial reporting in Nigeria. The scams at Lever Brothers (Nig) Plc and Afri Bank Plc are two examples of additional instances of dishonest financial reporting in Nigeria (Etim, 2013).

Several models used by Nigerian auditors in the detection and potential prevention of accounting fraud and errors have been evaluated and established by the auditing profession and various researchers. Regression, decision trees, neural networks, Bayesian networks, and supported vector machines are among the well-established and widely used models, according to Zhou and Kapoor (2011), as mentioned by Sahiti and Bektashi (2015). Similar to this, Zack (2013) suggested implementing a thorough financial statement analysis that involves an examination of the horizontal, vertical, budget variation, and financial ratios. Additionally, Unegbu and Tasie (2011) examined and advised the use of "Cash Flow Statement and Percentage Trend Analysis" for its identification in an effort to stop the rising rate of fabricated financial statements.

Benford's law is one of these possible models. The domestic research environment is silent on the subject, despite the fact that the potential effectiveness of the law has been demonstrated in the international literature. As a result, using Cadbury Nigeria Plc as a case study, this research explores the possible efficacy of Benford's Law in the detection of abnormalities in accounting data supplied by Nigerian corporations.

However, experts contend that existing models' capacity for detection has deteriorated with time (Amiram, Bozanic, & Rouen 2015). Yin (2016) hypothesises that the fact that present detection models have been researched for a considerable amount of time may be one factor in the decreased detection performance of existing models. As seen in Smith's (2013) lessons from the HealthSouth fraud, staff members engaging in fraudulent activities have become more knowledgeable about these models over time and have developed ways to carry out these fraudulent acts in a way that would evade the auditors' notice. Therefore, a new model is required that warns against manipulating and making attractive the entries on financial statements.

1.2. Objectives of the Study

The main objective of this study is to evaluate the potential effectiveness of Benford's law in the detection of accounting data fraud in the Nigerian setting.

The specific objectives are to:

- Examine Benford's law usage on real life data.
- Analyze the applicability of Benford's law to Nigerian accounting data.
- Test the conformity of accounting data to Benford's law.
- Determine the effectiveness of Benford's law in the detection of fraudulent accounting practices in Nigeria.

1.3. Research Questions

In view of the research objectives outlined above, the following are the research questions guiding this study:

- How is Benford's law being applied to real-life data?
- Is Benford's law applicable to accounting data?
- Does accounting data conform to Benford's law?
- Is Benford's law effective in the detection of accounting data fraud in Nigeria?

1.4. Hypotheses of the Study

For the study, the following hypotheses were developed and given in the null form:

H01: Nigerian accounting data does not notably follow Benford's law.

H02: Benford's law is not important for identifying accounting fraud in Nigeria.

1.5. Significance of the Study

Through the use of an old but little-known model that most fraudsters are unaware of, this study will assist auditors and forensic accountants in their efforts to spot irregularities in the financial records of firms, giving the man the advantage over the fraudsters.

In their coordinated efforts to combat corruption in organisations and the country at large, anti-corruption agencies and regulatory authorities like the Economic and Financial Crimes Commission (EFCC), the Central Bank of Nigeria (CBN), and the Independent Corrupt Practices Commission (ICPC) will find great value in the study.

The study will also be very helpful to anyone who uses financial information, such as business owners, shareholders, investors, business analysts, etc. They can use Benford's law to find fabricated financial statements and use that information to make better decisions.

In addition to contributing to the advancement of knowledge, this study will serve as the foundation for future studies on the application of Benford's law and the detection of accounting data fraud in Nigeria. It will increase the body of knowledge on the subject and serve as a source of information for more empirical research.

1.6. Scope and Limitation of the Study

With particular reference to Cadbury Nigeria Plc, the study's main objective is to assess the possible efficacy of Benford's law in the identification of accounting fraud in Nigeria.

We'll look at the financial statements of Cadbury (Nig) Plc from 2003 to 2020, which were divided into five main clusters with three years of financial statements each.

Financial statements from 2003 to 2005 that were suspected of containing financial data fraud make up the first cluster of three years. Financial statements from the second, third, fourth, and fifth clusters of three years, respectively, range from 2006 to 2008, 2012 to 2014, 2015 to 2017, and 2018 to 2020, and are each found to be free of financial data fraud.

There are certain limitations to this study. First, the small sample size is a limitation of this study. The sample size was reduced significantly due to time constraints. Data analysis is very time-consuming, as it requires manual data entry to test for compliance with or divergence from Benford's Law. The significant reduction of sample size may cause biases in the final data as Benford's Law is valid with larger sample sizes. A broader study is required to establish the effectiveness of the tool across all firms.

Second, the sample was not selected at random, which can have an impact on how broadly the findings can be applied. Because the status of "errant" and "compliant" financial statements was known beforehand thanks to the advantage of hindsight, the data gathering approach may involve an obvious source of sample bias. This begs the question of whether the test method, that is, as a prediction and/or detection tool, would be as trustworthy in the case of live data.

Third, the researcher's access to the necessary data for additional tests on the efficiency of the law will be hampered by the confidentiality of false financial statements in Nigerian businesses. The results of this investigation, however, make it very evident that the law can be used to spot accounting data fraud.

2. REVIEW OF LITERATURE

2.1. Conceptual Review

The various key factors, concepts, or variables relevant to this work and the presumed relationships among them are discussed in this section.

2.1.1. Fraud

Many authorities have tried to define fraud as it pertains to them because the concept and nature of fraud in and of itself are diverse, spanning practically all spheres. In the broadest sense, fraud can be defined as any crime committed for financial gain and using deceit as its primary method of operation (Wells, 2017). Fraud was described as "the intentional deception to induce a person to give up property or some legal right" by Webster's New World Dictionary.

Fraud may be defined as any deception used to cheat or deceive another person to their own or another person's detriment, or to cause another loss or injury, while the perpetrator is aware of their deliberate falsehoods, deceptions, or advantage over the innocent and unsuspecting victim. Individuals and organisations commit fraud to acquire money, goods, or services; to avoid payment for goods or services; to prevent the loss of services; or to gain a personal or professional advantage (Etim & Ihenyen, 2013).

According to Stanley (1994), fraud is the deliberate fabrication of materially false information with the intention of leading a third party to act in accordance with the false information, causing loss or damage. According to Hamilton and Gabriel (2012), who cited Radzinowicz and Wolfgang (1997), fraud and white-collar crime are both illegal acts that are characterised by guilt, concealment, and deceit and do not require the use of physical force, violence, or threats of such. According to Gupta (2013), fraud is also described as an intentional conduct intended to persuade another person to give up something of value or a legal right, as well as a purposeful misrepresentation or concealment of information with the objective to deceive or mislead.

According to Black's law dictionary, fraud is a knowing misrepresentation of the truth or concealment of the material fact to induce another to act to his or her own detriment. Mr. Mircea N. Costin, in his "Dictionary of Civil Law," defines fraud as an intentional violation by the parties of the mandatory provisions of the legislation in force, often by using perfidious means, at the conclusion or execution of a legal act. From the foregoing definitions, it can be deduced that fraud is a broad legal concept; this research work is concerned with fraud that causes a material misstatement in the financial statements, which can be referred to as "accounting data fraud."

2.1.2. Accounting data fraud

Several experts, academics, and authorities have described accounting data fraud. Accounting data fraud was defined by The Association of Certified Fraud Examiners (ACFE) in 2012 as the intentional misrepresentation of an enterprise's financial condition through the purposeful omission of amounts from the financial statement of the organisation in order to deceive financial statement users. Accounting data fraud is defined by the American Institute of Certified Public Accountants (AICPA) as "purposeful conduct that results in a serious falsification of the financial statements" in SAS No. 99, "Consideration of Fraud in a Financial Statement Audit," published in 2002.

Accounting data fraud, according to Gupta (2013), is the intentional attempt by corporations to defraud or mislead readers of published financial statements, particularly investors and creditors, through the preparation and distribution of materially misstated financial accounts. According to Wells (2017), accounting data fraud is the intentional misstatement or omission of financial statement quantities or disclosures with the intent to deceive users of financial statements, notably creditors and investors. According to Elliott and Willingham (1980), who were quoted by Intal and Do (2012), accounting data fraud is frequently carried out by management or with their knowledge and cooperation.

Schemes involving the intentional misuse of accounting principles, policies, and procedures used to measure, recognise, report, and detect economic events and business transactions include forgery, alteration, or manipulation of financial records, supporting documents, or business transactions; intentional material omission or misrepresentation of events; and forgery, alteration, or manipulation of accounts or other important information from which financial statements are prepared (Etim & Ihenyen, 2013).

Public statistics on the potential costs of accounting data fraud, including those from the 2015 Global Fraud Survey, show that the impacted organisations will suffer severe direct and indirect losses as a result. For instance, according to Albrecht and Searcy (2001), more than half of U.S. corporations suffer fraud losses of more than \$500,000; Enron, World Com, Quest, Global Crossing, and Tyco collectively lost \$460 billion to shareholders while losing about \$70 billion in market capitalization to investors, employees, and pensioners (Cotton, 2002).

Wells (2017) claims that some severe impacts of this fraud include decreased confidence in the capital markets, negative effects on the growth and prosperity of the country, bankruptcy or significant economic losses, etc. In addition to the obvious financial losses, he also emphasised the various expenses associated with accounting data theft, including legal fees, higher insurance premiums, lost productivity, poor effects on staff morale, consumer goodwill, supplier trust, and adverse stock market reactions.

2.2.3. Types of accounting data fraud

In 2002, the American Institute of Certified Public Accountants (AICPA), in its Statement of Auditing Standards (SAS) No. 99, "Consideration of Fraud in a Financial Statement Audit," highlighted two relevant types of accounting data fraud: misstatements arising from fraudulent reporting and misstatements arising from misappropriation of assets.

Misstatements arising from fraudulent financial reporting: AICPA (2002) defines these as deliberate understatements or omissions of amounts or disclosures in financial statements intended to deceive financial statement users, which have the effect of preventing the financial statements from being presented in accordance with generally accepted accounting principles in all material respects (GAAP). According to Wells (2017), fraudulent financial reporting can be accomplished in one of three ways: by using the accounting system as a tool to generate desired results, by feeding false and fictitious information into the accounting system to manipulate reported results in a way that is more significant than can be accomplished by simply playing the accounting system, or by completely disregarding the accounting system's rules. Spathis (2002, as cited by Brennan & McGrath, 2007) identified three major methods of committing financial statement fraud: changing accounting methods, altering managerial estimates, and improper recognition of revenue and expenses.

As stated by the International Standards on Auditing 240 (2009), management could also perpetrate this fraud by overriding controls using techniques such as;

(i) Recording fictitious journal entries, particularly close to the end of an accounting period, to manipulate operating results or achieve other objectives; (ii) Engaging in complex transactions that are structured to misrepresent the financial position or financial performance of the entity;

(iii) Inappropriately adjusting assumptions and changing judgements used to estimate account balances

Generally, according to Etim and Joseph (2015), falsification of accounts may be resolved by:

(i) Utilizing secret reserves during a time when a company's profits were lower without letting shareholders know; (ii) allocating revenue expenses to capital accounts or vice versa; or (iii) crediting the revenue account with income that will be received in the following year rather than the profit and loss account with accrued but unpaid income.

The asset misappropriation fraud case involving Koss Corporation, a Wisconsin-based manufacturer and supplier of stereo headphones from 2005 to 2009, demonstrates how Zack (2013) claims misstatements from fraudulent financial reporting could also be used to conceal asset misappropriation. He claimed that it might also be used to cover up unlawful behaviour in the same manner.

Misstatements arising from misappropriation of assets*:* It involves the theft of an entity's assets when the outcome of the crime results in the financial statements not being presented, in all relevant aspects, in compliance with GAAP. This is also known as asset theft, asset distortion, or asset defalcation (AICPA, 2002). In order to hide the fact that the funds are missing, Kwok (2005) claims that misappropriations of assets frequently come with fraudulent or deceptive records or paperwork. This indirectly results in accounting inconsistencies in financial accounts. Employees typically misappropriate assets in relatively modest and insignificant amounts (Kassem, 2014). However, management may also be involved because they are frequently better able to cover up or disguise thefts in ways that are difficult to spot (Soltani, 2007; Beasley *et al.*, 2010; Jones, 2011; Kassem, 2014).

The International Standards on Auditing 240 (2009) posits that misappropriation of assets can be accomplished by various means, such as embezzling receipts, stealing tangible (physical) assets or intangible (e.g., intellectual property), payments to fictitious employees, vendors, or customers, sale at overestimated prices, and among others.

Asset misappropriation is divided into three more sub-categories based on a 1995 study by Wells: skimming schemes, cash larceny, and fraudulent disbursement scams (Kassem, 2014). Skimming, which is frequently referred to as an "off-book strategy," is exceedingly challenging to identify, look into, and prove since it occurs before money is recorded in an organization's accounting system, leaving no audit trail. Unrecorded or underestimated sales and receivables may be a component of skimming (Wells, 2017). Contrarily, cash larceny, the second subtype of asset misappropriation, is the theft of money that has already been entered into an organization's accounting system. Thus, cash larceny is called an "on-book scheme" (Wells, 2005; Silverstone & Sheetz, 2007; ACFE, 2010; Kassem, 2014). The third sub-category of asset misappropriation is called "fraudulent disbursement." In this scheme, the perpetrator causes his or her organisation to disburse funds through some tricks or devices (Wells, 2005; Silverstone & Sheetz, 2007; ACFE, 2010; Kassem, 2014).

2.1.4. Cadbury (Nig.) Plc accounting scandal

An accounting controversy involving Cadbury (Nigeria) Plc. resulted in a massive and intentional overstatement of the company's profit by more than N13 billion (US $96.30 million) between the years 2003 and 2006. (see Business Day, 9 January 2007). When Cadbury Schweppes Plc International, the parent firm, raised its investment in Cadbury Nigeria Plc, the financial crisis at that company came to light. In order to consolidate its accounts in Cadbury Nigeria Plc in light of this new shareholding by the parent company, the parent company had to become involved in the running activities of Cadbury Nigeria Plc (Bakre, 2007). The board of Cadbury Nigeria PLC informed the Commission, its stockholders, and other regulatory organisations of the finding of "Overstatements" in her accounts in November 2006. According to the board, these overstatements reportedly extended for many years (Salaudeen, Ibikunle, & Chima, 2015). As a result, the board of directors hired Price Waterhouse Coopers to assess and look into the financial status of Cadbury Nigeria Plc (see Business Day, January 9, 2007).

By giving Cadbury Nigeria Plc a "clean bill of health" throughout these times, the external auditor, Akintola Williams Deloitte, has once again come under fire, according to further investigations (see Vanguard, January 9, 2007). More information was disclosed, including the fact that Cadbury Nigeria Plc actually lost N5 billion (US$37.04 million) over the course of the time despite the management of the firm reporting enormous profits to shareholders under the guidance of Akintola Williams Deloitte (New Nigerian News, 12 December 2006).

Cadbury (Nigeria) Plc is a for-profit company; therefore, its management was under pressure to increase profits, present a strong financial sheet, and enrich itself. To alter its financial report, they used stock buybacks, cost deferrals, trade loading, fictitious supplier certifications, asset concealment, bank balance inflation, and rights issues. A balance of N7.7 billion was credited to the company's account in 2005 without any bank's confirmation of the bank balances. Cadbury management had an offshore account that was completely removed from the company's accounts and used to top up the salaries of the executive directors. To make such payments to the directors, the board's compensation committee's approval was not required. The chief cooks were members of top management, specifically the managing director and chief financial officer. They were supported by other members of top management and middle management.

The Director General of the Nigerian Stock Exchange, Okereke-Onyiuke, stated in response to this controversy in 2007: "Our auditors should receive some of the blame, even if it is difficult for them to detect all the abnormalities in the accounts of companies."

Nevertheless, despite the difficulties they face, auditors must go above and beyond to delve into the financial records and transactions of the organisations that are submitted to them. We are aware that auditors work on the documentation that management of companies presents to them, but over the course of their audits at the firm, auditors have the opportunity to interact with some of the personnel who are not management staff to learn more about the company.

2.1.5. An overview of Benford's Law

Various names for the law have been used, including "first-digit law," "law of leading digits' frequencies," "significant digit law," and even "digital frequencies analysis" (Nigrini, 2011). The distinctive feature of Benford's law is that it can only be observed in naturally occurring numbers and not in made-up numbers. As a result, Benford's law might be considered a true hallmark of nature that the human brain cannot manually reproduce (Kumar & Bhattacharya, 2003).

In 1881, American astronomer and mathematician Simon Newcomb first discovered the law of the first digit, which he noticed in log tables used in mathematics and physics. He published a short article in the "American Journal of Mathematics" describing his observation that books of logarithms were more worn in the beginning and progressively unspoiled throughout (Newcomb, 1881; Benford, 1938; Hill, 1995; Nigrini, 2012; Miller, 2015). He also observed that numbers with a first digit of 1 were observed more often than those starting with 2, 3, and so on. From these, he inferred that low numbers occur more frequently than high numbers. On that basis, he developed a set of mathematical theorems to determine the distributions of numbers appearing in different digital positions within naturally occurring figures, which produced the result that the probability of a single number, N, being the first digit of a number was equal to log(N+1)–log(N). Despite the profound insights offered, his research did not attract the attention of the academic community as he did not endeavour to explain his observations.

Frank Benford, an American mathematical physicist, made the same discovery over 50 years after Newcomb did while perusing the first few pages of his own logarithmic books. In contrast to his predecessor, Benford actively investigated this phenomenon and published his findings in a number of academic publications, sparking the curiosity of academics. As a result, the phenomena became known as "Benford's law," and Newcomb's name was forgotten (Kumar & Bhattacharya, 2003). Using a variety of data, including sets of rivers, population density, physical and mathematical constants, baseball statistics, birth and death rates, numbers in magazine articles, atomic weights, and street addresses, Benford set out to test his hypothesis. He collected 20,229 observations in total (Benford, 1938). He shown through his thorough investigation that as the value of the number in the first digit rises, so does the frequency of the first digit in a population's numbers. But it wasn't until 1995 that American scholar Hill offered a rigorous theoretical demonstration that the first number adhered to the fundamentals of Benford's law. He demonstrated inventive use of the effective numerical centre limit theorem in statistics. Hill (1995) demonstrates that, like the normal distribution, Benford's distribution is a phenomenon that can be empirically seen.

Benford calculated the specific probabilities that each of the nine digits was the first significant digit in a randomly observed naturally occurring number after analysing a massive amount of data to derive a logarithmic expression for the probability distribution function. The likelihood of coming across a number in which the n most significant digits represent the integer "d" is specifically determined by the Benford distribution. The following formula determines the linked random variable's probability:

$$P(d) = \log(d+1) - \log(d) = \log(1+d-1)$$

Where: d is a number 1, 2 …9, and P is the probability

Interestingly, there is also a general significant digit law which includes first digits and also higher order digits (which may be equal to 0) (Hill, 1996; Saville, 2006). For example, the general law holds that the probability that the second significant digit (d2) of a number is equal to:

$$P(d_2) = P(d_2) = \Sigma_{d1=1}^{9} \log_{10}\left(1+\frac{1}{d_1 d_2}\right)$$

Where $d_2 \in \{0, 1, . . ., 9\}$

From this general law, it follows that the second significant digits, although monotonically decreasing in frequency through the digits (as in the case of the first digits), are much more uniformly distributed than the first digits (Saville, 2006). To illustrate this point, the table below shows the expected frequencies for all digits 0 through 9 in each of the first four places in any number based on Benford's law.

Table 1: Probabilities of first and higher order significant digits

Digit (d)	*Probability of first significant digit = d*	*Probability of second significant digit =d*	*Probability of third significant digit =d*	*Probability of fourth significant digit =d*
0	Not Applicable	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	0.10031	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

Source: Nigrini (1996). A taxpayer compliance application of Benford's Law. *The Journal of the American Taxation Association,* 18 (1): p74

2.1.6. Characteristics of a Benford's set

According to Tammaru and Alver (2016), a data set that corresponds to Benford's law is generally referred to as a Benford's set and should possess the following characteristics:

- Scale invariance: Multiplying all values in Benford's set by any constant also creates Benford's set, as described by Pinkham (1961). This Benford's law property is particularly relevant with respect to the change of unit of measurement (for example, converting from English to metric units or from yen to euros).
- Base invariance: Hill was able to provide evidence that Benford's Law is invariant under changes of base (for example, replacing base 10 by base 8 or base 2, in which case the logarithmic base 10 is replaced by the logarithm to the new base) (Hill, 1996; Saville, 2006).
- Sum invariance: Nigrini (2012) remarked that in tables of data distributed according to Benford's law, the sum of all elements with the first digit or digits is approximately constant.

2.1.7. Application of Benford's Law to real life data

Not all substantial, unaltered real-world data sets automatically adhere to Benford's law. Benford's law can be applied to collections of numbers that have particular properties, according to research that has sought to apply it to a variety of data sets (Talwar & Mehta, 2015). Wallace (2002) noted that a data set is more likely to follow Benford's distribution if its mean is higher than its median and if skewness has a positive value. If the following criteria are met, close compliance with Benford's law can typically be anticipated, according to Nigrini (2011).

- All data must be recorded in the same unit. This implies that all data must describe the same phenomenon.
- The data set should not contain any built-in minimum or maximum values for the data, except perhaps for a minimum of 0 for data that can only be made up of positive numbers. For example, a stockbroker that has a minimum commission charge of $50 for any buy or sell transaction would have many people whose small trades attract the $50 minimum. A data set of the commission charges would have an excess of first digit 5s and second digit 0s.
- The data set should not include any assigned numbers. Assigned numbers have the purpose of identification and do not therefore arise

from any natural calculation process. Thus, ID codes, bank accounts, and telephone numbers do not conform to Benford's distribution.

- A data set should tend to have more small than large numbers, which also accords with the natural development process. For example, it can be expected, in general, that small invoices are found more often than large ones. The rule that there are more small records than large records is true in general in that there are more towns than big cities, more small businesses than giant companies, and more small lakes than big lakes. Nonetheless, the data set does not have to be disseminated widely (Raimi, 1976).

According to the information above, a Benford distribution is predicted to fit the majority of accounting-related data. However, a Benford distribution does not apply to all populations of accounting-related data. First, due to its established modes, this law is not followed by numbers that are impacted by mental processes, such as the quantity of checks, the cost of things, and ATM withdrawals (Nigrini & Mittermaier, 1997). Second, when the data has a forced maximum or minimum, Benford's analysis should not be used. When accounting limitations are present, Benford analysis can only be applied to global data and not to data about specific individuals because global data does not have enforceable limits. Third, salary information does not follow Benford's Law because most workers in the same industry, such as hotel staff, teachers, and police officers, make about the same salary. However, if we examined the salaries paid by a global company, such as General Electric, with many levels of employees in many nations and in many currencies, pay and compensation statistics might adhere to Benford's Law.

In general, results from Benford analysis are more reliable if the entire account is analysed rather than sampling the account. This is because the larger the number of transactions or items in the data set, the more accurate the analysis.

2.1.8. Benford's law and detection of accounting fraud

Data from many different fields has been proven to be consistent with Benford's law. Hill (1995) demonstrated that the financial data set may also be used to apply this law. Hill noted that Benford's distribution resembled the normal or Gaussian distribution and that the majority of accounting-related data is likely to follow this pattern. Due to the frequency of the logarithmic distribution in real accounting data sets, Benford's Law is now used internationally to identify financial document fraud and data fabrication on the theory that those who create data do not pick values that conform to the logarithmic distribution (Hill, 1995; Talwar & Mehta, 2015).

The digit distribution of data is compared to a Benford distribution using the Benford analysis methodology. According to Benford's law, alarms are raised if there is a significant deviation from the expected distribution since this suggests the effect of an outside source. As a result, Benford's analysis is frequently the first step in a forensic audit because it identifies places to start for more thorough analysis and evidential searches, as suggested by Nigrini (1999).

Etteridge and Srivastava (1999) demonstrated, however, that an accounting data set that deviates from the Benford distribution may not necessarily be a sign of fraud. Instead, it would highlight specific operational shortcomings or structural problems. The rationale for applying Benford's Law to identify unexpected patterns in accounting transaction activities was presented by Nigrini and Mittermaier in 1997. An individual creating fraudulent entries is very likely to invent a string of fictitious figures to increase his expenses and will attempt to make them appear "natural" by distributing the first digits evenly between 0 and 9. Because the ultimate goal is to correct for the anomalies caused by the misuse of cash, the numbers manufactured to "balance the books" in more sophisticated frauds, like the one involving HealthSouth, are also essentially unnatural. Of course, his numbers won't follow Benford's Law, but in such a case, the auditor might find the fraudulent transactions due to the change in the first and second digits of the Benford's Law probability distribution. Furthermore, it is generally known that people do not behave completely randomly, even when it is to their advantage (Bakan, 1960; Neuringer, 1986; Hill, 1999). As a result, there is a higher chance that accounting fraud will be discovered when the law is applied.

2.2. Theoretical Review

This section consists of the corpus of theory that has accumulated in regard to this concept and theory, which forms the bedrock of this study. The study is conducted through the lenses of Pinkham's scale invariance theorem, the "Random Samples from Random Distributions" theorem, and fraud theories.

2.2.1 Fraud theory

Over the past few decades, fraud theory has evolved in an effort to explain why corporate fraud can happen within a corporation (Christian, Basri, & Arafah, 2019). The idea of the fraud triangle, put forward by Cressey in 1953, formed the foundation for the literature on fraud theory. Later, Wolfe and Hermanson (2004) established the theory of diamond fraud, while Crowe and Howarth (2007) produced the theory of pentagon fraud (2011). In this study, the fraud theory is used because it offers a good framework for examining why people committed fraud in the 1950s. The Fraud Triangle was created by renowned criminologist Donald R. Cressey (Abdullahi & Mansor, 2015). According to Cressey (1953), the three causes of fraud are pressure, opportunity, and rationalisation (Puspasari, 2016).

Wolfe and Hermanson evolved the Fraud Triangle Theory into the Fraud Diamond Theory in the CPA Journal in December 2004. According to Wolfe and Hermanson (2004, as referenced by Abdullahi & Mansor, 2015), fraud is unlikely to occur unless the fourth ingredient (i.e., capability) is also present, even when felt pressure may exist alongside an opportunity and a rationale.

The pentagon fraud hypothesis, developed by Crowe Howarth in 2011, represents the last stage in the evolution of fraud theory. Competence and arrogance are two additional components added by this approach. The capability mentioned in the fraud diamond theory by Wolfe and Hermanson in 2004 has the same meaning as the competence provided in this fraud pentagon theory (Muhsin & Ahmad, 2018). Competence or capability refers to an employee's capacity to flout internal controls, devise a cover story, and manipulate social dynamics for personal gain. Arrogance, on the other hand, is a superior attitude toward one's rights and the belief that one is exempt from business internal controls or standards (Muhsin & Ahmad, 2018).

2.2.2. Pinkham's scale invariance theorem

When scales of length, energy, or other variables are multiplied by a common factor, objects or laws are said to have scale invariance, which is a property that denotes universality in physics, mathematics, and statistics. The mathematician Roger Pinkham of Rutgers University asserted as a presumption in 1961 that if there were a law regulating digital distributions, it would have to be scale invariant, or independent of units (Nigrini, 2012). Scales and bases are cultural, arbitrary, and do not represent any fundamental properties of numbers or nature, according to scale and base invariance arguments, which contend that if there is a universal law for significant digits, it should be independent of units, scales, and the base in the number system used by society (Kossovsky, 2014).

Pinkham's claim implies that if we multiply all our numbers by an arbitrary constant, then the distribution of first-digit frequencies should remain unchanged.

Benford's Law is scale-invariant under multiplication, as demonstrated by Pinkham in 1961. As a result, the new list would also be a Benford set if all the numbers in a field that obeyed Benford's law were multiplied by a nonzero constant. Benford's Law, according to Hill (1995), is the only probability distribution on significant digits that is unaffected by changes in base (such as replacing base 10 with base 8 or base 2, in which case the logarithmic base 10 is replaced by the logarithm to the new base) or scale (such as changing from English to metric units or from Yen to Euros) (Hill, 1995). This theory, which explains a significant aspect of the Benford set, is unquestionably important to this study.

2.3. Empirical review

Benford's law has been frequently used in the last 20 years or so in accounting, auditing, corporate finance, and economics as a way to spot fraud, inconsistencies, and tampering with data reporting. The current section discusses the different ways that Benford's law has been applied in some of the aforementioned fields while also emphasising some pertinent literature that has already been published.

Table 2: Summary of Empirical Literature

S/N	*Author(s)*	*Title*	*Objectives*	*Methodology*	*Findings*	*Recommendation*
1	Carslaw (1988)	Anomalies in Income Numbers: Evidence of goal Oriented Behaviour	To determine conformity of income figure to Benford's law to examine the tendency of managers to round up income figures.	Z-Statistics and Chi-Square	Income figures with human manipulation do not conform to Benford's law. Managers tend to round up income figures when it is below a particular psychological threshold.	Benford's law should be used an indicator of rounded up income figures in annual reports.
2.	Nigrini (1994)	Using Digital Frequencies To Detect Fraud	To examine the use of Benford's law in the detection of accounting data fraud	Z-statistics and Mean Absolute deviation (MAD)	Deceitful numbers deviate significantly from Benford's law.	Benford's law should be use in the detection of accounting data fraud.

S/N	*Author(s)*	*Title*	*Objectives*	*Methodology*	*Findings*	*Recommendation*
3.	Saville (2006)	Using Benford's Law To Detect Data Error And Fraud. An examination of companies Listed on the Johannesburg Stock Exchange	To test the effectiveness of Benford's law in the identification of false or fraudulent reporting of accounting data.	Linear Regression Analysis and T-test	Data of errant companies failed the test of conformity while the data set with top reporting standards passed the test	Benford's law should be applied as an indicator of accounting data error and /or fraud.
4.	Linville (2008)	Problem of False Negative Results in the Use of Digit Analysis	To examine the effectiveness of common digit analysis technique (Benford's) law in detecting the presence of suspicious data.	Z-statistics	Digit Analysis (Benford's law) failed to detect the presence of suspicious data unless the percentage of data in the population in large (>10%)	Auditors should employ other techniques in conjunction with the digit analysis technique (Benford's law) for enhanced effectiveness.
5.	Krakar and Zgela (2009)	Application of Benford's Law in Payment Systems Auditing	To test the conformity of payment messages amounts to Benford's law.	Chi-square, Z-statistics and Mean Absolute Deviation (MAD)	Analysis of foreign payment messages without focus on special types of messages or certain business entities do not conform to Benford's law.	Benford's law is effective in audit of information systems, specifically foreign payment system. Auditors should perform some additional tests for certain digits which deviate from Benford's law frequencies in order to check against fraudulent or erroneous activity.

Source: Researchers' Compilation, (2022)

Table 2: Cont'd Summary of Empirical Literature

S/N	*Author(s)*	*Title*	*Objectives*	*Methodology*	*Findings*	*Recommendations*
6.	Hussain (2010)	The Application of Benford's law in Forensic Accounting: An Analysis of Credit Bureau Data	To examine the application of Benford's law in forensic accounting.	Chi-square	The observed frequencies were significantly different from the expected Benford frequencies.	Benford's analysis could be used in identification of suspected and manipulated accounts. Further Study on other digital analysis techniques and forensic accounting should be carried out.
7.	Henselmann, Scherr, and Ditter (2013)	Applying Benford's Law to Individual Financial Reports: An Empirical Investigation on the Basis of SEC XBRL Fillings	To analyze monetary items contained in SEC XBRL 10-k fillings for conformity to Benford's law.	Chi-square, Z-statistics and Mean Absolute Deviation (MAD)	On an average, the distribution conforms very well to the expected distribution according to Benford's law.	Several test statistics should be used for measuring the goodness of fit to Benford's law. Analysis procedures based on Benford's law should be applied to accounting data.
8.	Asllani and Naco (2014)	Using Benford's Law for Fraud Detection in Accounting Practices	To examine the effectiveness of a proposed tool based on the principles of Benford's law for fraud detection in accounting practices.	Z-statistics	Benford's law can be used as an effective tool to target potential areas of concern in accounting data for the purpose of fraud detection.	Benford's law should not be used as the only tool for accounting audits rather, as a complementary tool.

Source: Researchers'Compilation, (2022)

Table 2: Cont'd Summary of Empirical Literature

S/N	*Author(s)*	*Title*	*Objectives*	*Methodology*	*Findings*	*Recommendations*
9.	Egbunike and Amakor (2013)	Fraud and Auditors Analytical Procedure: A Test of Benford's Law	To examine the use of Benford's law as a tool for fraud detection and prevention in corporate organizations To determine whether statistical techniques provide auditors with greater fraud detection ability than conventional techniques or not.	Benford's law V 2.0 Software and Two Way analysis of Variance	Benford's law is useful in fraud detection and as a statistical tool to be employed in audit analytical procedure. Statistical techniques provide auditors with greater fraud detection ability than conventional techniques.	Benford's law should be employed in the audit of analytical procedure. Conventional audit techniques should be replaced with more appropriate data mining approaches to match the operating capacity of 21st century operations.
10.	Talwar and Mehta (n.d)	Devising a Model for Accounting Fraud Detection based on Benford's Law	To recommend an additional due diligence tool in order to identify the possibility of fraud on the basis of financial statements.	Chi-square, Z-statistics and kolmogorov-Smirnov (KS) Test	Financial statements of "good" companies conform to Benford's distribution while financial statements of "fraudulent" companies deviate significantly from Benford's law.	The proposed model based on Benford's law should be applied for accounting data fraud detection.
11.	Mate, Sadaf, Tarnoczi, and Fenyves (2017)	Fraud Detection by Testing the Conformity to Benford's Law in the Case of Wholesale Enterprises	To examine whether the conformity to Benford's law of forensic accounting data is sustentative in the case of wholesale trade enterprise	Mean Absolute Deviation (MAD)	Forensic accounting data does not conform to Benford's law and it is unsustainable the case of wholesale enterprises.	Further research should be carried out in the wholesale trade sector and more models proposed for the analysis of forensic accounting data.

Source: Researchers' Compilation, (2022)

Table 2: Cont'd Summary of Empirical Literature

S/N	Author(s)	Title	Objectives	Methodology	Findings	Recommendations
12.	Grammaikos and Papanikolaou (2015)	Applying Benford's Law to Detect Fraudulent Practices in the Banking Industry	To examine the dark side of banking statistics using Benford's law to detect possible data tampering.	Descriptive Statistics and Mean Absolute Deviation (MAD)	Managers and Board members have a tendency to falsify data on the profitability and size of their banks with possible purpose to misinform investors, regulators and market participants especially during crises.	Models with regulatory signals to consider strategic misinformation and for establishing independent agencies to assure the delivery of high quality banking data should be introduced. An amendment of SOX towards a stricter framework regarding bank profitability.
13.	Montano (2017)	Forensic Analytics of Financial Report in Philippines property Sector: The Benford's Law Application	To test the conformity of the property sector financial statements to Benford's law	Chi-square and Mean Absolute Deviation (MAD)	Income statement did not conform to Benford's law indicating misreporting of income statement in the property sector.	Benford's law should be used as a tool for detection of financial misreporting among property companies

Source: Researchers' Compilation, (2022)

Table 2: Cont'd Summary of Empirical Literature

S/N	*Author(s)*	*Title*	*Objectives*	*Methodology*	*Findings*	*Recommendations*
14	Cabarle (2018)	Using Benford's Law to predict the Risk of Financial Statement Fraud in Equity Corwdfunding Offerings	To examine the use of Benford's law in the identification of high and low risk in equity crowdfunder's financial statements provided to investors	Chi-square, Kolmogorov-Smirnov (KS) Test and Mean Absolute Deviation (MAD)	Regulation crowdfunding firms are more at risk for fraudulent financial reporting than other public firms, start-ups are a higher fraud risk than growing or maturing companies No specific funding tier is indicative of a higher or lower fraud risk, however fraud risk is equally pervasive in all tiers.	Benford's law should be applied to ongoing annual reporting and trend analysis in order to find anomalies. Further investigation on the relationship between independent variables and the risk of fraud such as the type of securities offered.
15	Ozevin, Yucel, and Oncu (2020)	Fraud Detection with Benford's Law: An Alternative Approach with BDS and Critical Values	To create alternative standard and critical values that can be used to assess financial data compliance with Benford's law	Mean Absolute Deviation (MAD)	The new measuring standard BDS and conformity limits are more effective for audit aims.	The conformity limits should be used in the evaluation of financial statements and their compliance with Benford's law on the large data set for enhanced effectiveness.

16	Cunningha and Bennett (2021).	Using Benford's law to detect falsification of data in Iran Coronavirus Report	To investigate authenticity of reported Covid-19 cases I nIran	Examination of Hospital records for documented evidence (Secondary Data)	Existence of inconsistence in recorded cases and public expenditure	Transparency in documenting relevant for effective planning
17.	Farhidi (2021)	Can we rely on Covid-19 Data?	An assessment of data from different countries to test Benford's law	Analysis of secondary data using SEM technique	Conformation of use of Benford's Law to detect data fraud	Need to apply the Benford's law in all data
18.	Kilani (2021a)	An interpretation of Reported Covid-19 cases in post-soviet states	Using Benford's law to detect data errors	Reviews of secondary data and applying Benford's digit codes	Existence of data manipulation in reported Covid-19 reports	Need for transparency in handling public health issues
19.	Kilami (2021b)	Authoritarian Regimes propensity to mangulate Covide-19 Data: a statistical analysis using Benford's Law	To assess the applicability of Benford's law in detecting data manipulation	Descriptive analytical technique in examining secondary data	Presence of data management in both social and economic data	A call for morality and ethical disposition in data management.
20.	Damla (2022)	Benford's Law: An Empirical Analysis of reported Covid-19 cases and institutional structures around the globe	The aims was to use newcomer-Benford's Law (NBL) to detect inconstancies in data by testing the first-digit's comformity	Use of large dataset to test NBL Using Chi-square, Kuiper and mean absolute Deviation	Data conformity to NBL increases with per capita wealthy countries than poor countries, hence data manipulation is common with such countries	The applicability of NBL to all types of data economic, social, political and demographic for transparency in all presorting framework.

Source: Researchers' Compilation, 2022

2.5. Gap in literature

Benford's law has been widely applied to test different categories of data with the aim of assessing conformity and detecting error and/or fraud, with accounting and forensic data inclusive. In the past few decades, various researchers in an international setting have proved the effectiveness of this law in the detection of fraud and/or error in various categories of accounting data. However, little research exists on this topic in the Nigerian context.

The only domestic researchers who attempted to assess the use of Benford's law by auditors for fraud detection were Egbunike and Amakor (2013). However, they analysed financial statements of selected financial statements with no particular reference to any company. Also, there was no other evidence of the existence or nonexistence of fraud in the financial statements except for Benford's Law being tested. This raises the question of its reliability in the detection of fraud in individual Nigerian companies.

3. METHODOLOGY

This chapter highlights the various research methods, techniques, and procedures employed in the study. These include the research design, area and population of study, sample and sampling technique(s), sources of data collection, and data analysis technique(s).

3.1. Research design

This study adopted the ex-post facto research design. The ex-post facto research design was adopted because the study involves facts and events that have already taken place without interference or manipulation by the researcher.

3.2. Population of the study

The population of this study comprises the financial statements of Cadbury Nigeria Plc, which are quoted on the Nigerian Stock Exchange. Cadbury Nigeria Plc. was established in The population covers financial statements from 2003 to 2008 and 2012 to 2020, giving a population of 15 years.

3.3. Sample size and sampling technique

The purposive sampling technique was adopted for this study. This implies that the sample was not probabilistic and was selected deliberately by the researcher. The adoption of this purposive sampling technique was due to the fact that samples were selected based on availability and a predetermined criterion: errant or presumed compliant.

The sample comprises 15 years' worth of financial statements of Cadbury Nigeria Plc. between 2003 and 2020, grouped into 5 major clusters of three years' financial statements each. The first cluster comprises financial statements between 2003 and 2005, which were proven to contain accounting data fraud. The second cluster comprises financial statements between 2006 and 2008, which were assumed to contain restatements meant to correct the effects of the previous years' misstatements. The third, fourth, and fifth clusters comprise financial statements for 2012–2014, 2015–2017, and 2018–2020, respectively, that are presumed compliant and fraud-free.

3.4. Method of data collection

The data employed in the study were gotten solely from secondary sources. This study relied heavily on data generated from the annual financial reports of Cadbury Nigeria Plc, sourced from African Financials. Other sources of data were internet publications, which include journal articles, newspaper articles, textbooks, and videos.

3.5. Method of data analysis

Tables and charts were used in the analysis of the data extracted from the financial statements. The statistical tools employed for testing the hypotheses at 5% significance level are Z-Statistics and Chi-square test with 8 degrees of freedom respectively. This is done with the aid of the Microsoft Excel 2010 software package.

3.6. The Z-statistics

The Z-Statistics is performed to indicate any statistical difference between the observed distribution and the expected distribution. It tests the significance of the deviation for each digit or digit combination separately. The purpose of this test is to examine if the observations that are made would lead to the acceptance or rejection of the null hypothesis. It is determined as follows:

$$z(d_1) = \frac{|\, p(o) - p(e)\,| - \left(\frac{1}{2n}\right)}{\sqrt{\frac{p(e)(1-p(e))}{n}}}$$

where;

p (e) = expected proportion of digit frequency

p (o) = observed proportion of digit frequency

n = number of observations

N/B: The continuity correction term (1/2n) is only used when the term is smaller than the absolute value of the difference between the actual and expected proportion of digit frequency.

The Chi Square

The chi-square statistic shows the relationship between two data sets. It is often used to draw conclusions if two data sets, the observed data and the expected data, at a certain significant level with a determined degree of freedom, match or vary from each other. The purpose of this test is to examine if the observations that are made would lead to the acceptance or rejection of null hypothesis 2. It is determined as follows:

$$x^2 = \Sigma_{i=1}^{n} \frac{(n(o) - n(e))^2}{n(e)}$$

where;

$\sum$ = summation

n = number of possible digits

n(o) = observed digit frequency

n(e) = expected digit frequency according to Benford's law

3.8. Test of significance / Decision Rule(s)

For Z-statistics, if the resulting z score is less than the critical value at the 5% significance level, the null hypothesis is rejected, which implies that there is a significant relationship. Otherwise, fail to reject the null hypothesis, which implies a significant deviation.

i. For Chi-square, if the resulting X^2 value is less than the critical value at the 5% significance level, the null hypothesis is rejected, which implies that there is a significant relationship. Otherwise, fail to reject the null hypothesis, which implies a significant deviation. For Chi-square, if the resulting X^2 value is less than the critical value at the 5% significance level, the null hypothesis is rejected, which implies that there is a significant relationship. Otherwise, fail to reject the null hypothesis, which implies a significant deviation.

4. DATA PRESENTATION, ANALYSIS AND DISCUSSION OF FINDINGS

4.1. Introduction

This chapter includes a presentation, data analysis and interpretation, a test of a hypothesis, and a conclusion. The financial accounts of Cadbury Nig. Plc. were used to generate the data, which was then displayed as tables and figures. Hypotheses were assessed using first- and second-digit tests.

4.2. Data presentation

The data captured for the study included figures in the financial statements and notes to the accounts obtained from the annual reports of Cadbury Nigeria Plc. The study covers a period of 15 years (2003–2008, 2012–2020).

4.3. Benford's digit tests

The basic Benford's digit tests performed to identify the possibility of "accounting fraud" include the first digit test and the second digit test, which are analysed below:

4.3.1. First digit test

The First Digit Test is a high-level test of reasonableness with nine possible first digits from 1 to 9. The first digits of every number on the financial statements for the years were identified and analysed as follows:

Table 3: First Digit Analysis

First Digit	P(e)	2003-2005 P(o)	2006-2008 P(o)	2012-2014 P(o)	2015-2017 P(o)	2018-2020 P(o)
1	0.30	0.36	0.31	0.33	0.31	0.32
2	0.18	0.12	0.15	0.20	0.16	0.19
3	0.12	0.14	0.13	0.12	0.11	0.13
4	0.10	0.09	0.12	0.08	0.10	0.07
5	0.08	0.10	0.06	0.08	0.09	0.07
6	0.07	0.07	0.07	0.05	0.08	0.05
7	0.06	0.05	0.05	0.05	0.06	0.07
8	0.05	0.04	0.06	0.05	0.04	0.06
9	0.04	0.03	0.05	0.04	0.05	0.04

Where P(o) = observed proportion

P(e) = expected proportion based on Benford's law

Source: Researchers' Computation, (2022)

Graphical representation of first digit distribution

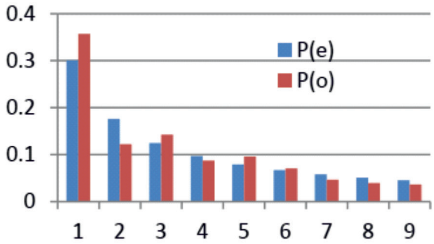

Fig. 1: f.d. Distribution 2003-2005

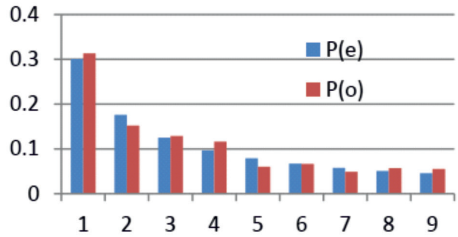

Fig. 2: f.d. Distribution 2006-2008

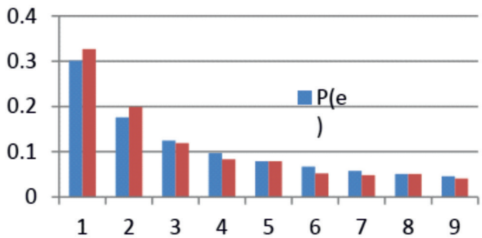

Fig. 3: f.d. Distribution 2012-2014

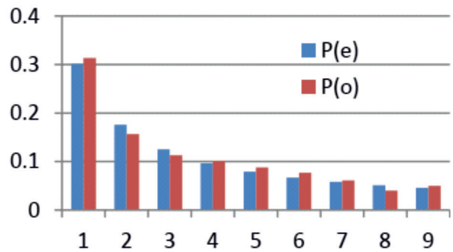

Fig. 4: f.d. Distribution 2015-2017

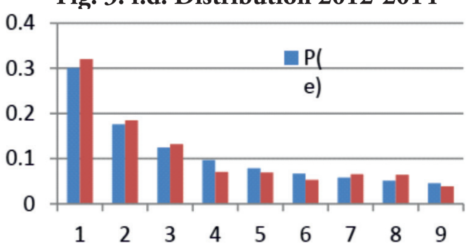

Fig. 5: f.d. Distribution 2018-2020

Table 3.1 and the graphical illustrations in figures 1–5 show the analysis of the first digits for the five clusters of years analyzed. For the first cluster (2003–2005), which are the years with errant financial data, the observed proportion deviates significantly from the expected proportion according to Benford's law. This is observable in Figure 1, where there is a spike in the observed proportion of digit 1 against the expected proportion and a significantly lower observed proportion of digit 2 against the expected proportion. This suggests an increased usage of the first two digits and less of the first digit for the earnings management that was carried out, which indicates human manipulation.

The second cluster comprises financial data for the years 2006–2008. Within these years, the earnings management carried out in previous years was discovered and adequate adjustments were made to eliminate the effect of the misstatements in the financial statements, which indicate a minimal level of human intervention. Consequently, the observed and expected proportions of the first digits as observed have a marginally acceptable conformity with some level of deviation due to the adjustments, as indicated by the graphical representation in figure 2.

The third, fourth, and fifth clusters comprise financial data for the years 2012–2014, 2015–2017, and 2018–2020, respectively, which are presumed to be compliant. The differences between the observed and expected proportion of first digits for the fourth and fifth clusters presented in Table 4.1 were between 0 and 0.02; these are statistically insignificant, hence an acceptable conformity. This conformity for the fourth and fifth clusters is easily observable with the visual representations in Figures 4 and 5, respectively.

However, the observed proportions of first digits 1 and 2 for the third cluster (2012-2014) are 0.33 and 0.2, respectively, against the expected proportions of 0.3 and 0.18, respectively, causing a spike in the observed proportion represented in Figure 3. The general rule is that a weak fit to Benford's Law is a flag that the data table contains abnormal duplications and anomalies. Hence, according to Benford's law, the financial statements in the first cluster (2003–2005) contain anomalies, while those in the other clusters do not.

4.3.2. Second digit test

The second-digit test is a second overall test of reasonableness, with 10 possible first digits from 0 to 9. This test is actually too high-level and, as such, has limited usage.

The second digits of every number on the financial statements for the years were identified and analyzed as follows:

Table 4: Second Digit Analysis

Second Digit	*P(e)*	*2003-2005 P(0)*	*2006-2008 P(o)*	*2012-2014 P(o)*	*2015-2017 P(o)*	*2018-2020 P(o)*
0	0.120	0.124	0.111	0.084	0.115	0.171
1	0.114	0.118	0.102	0.106	0.096	0.079
2	0.109	0.090	0.117	0.134	0.112	0.070
3	0.104	0.099	0.118	0.116	0.112	0.124
4	0.100	0.107	0.115	0.108	0.089	0.113
5	0.097	0.106	0.093	0.130	0.103	0.095
6	0.093	0.099	0.088	0.069	0.095	0.110
7	0.090	0.081	0.073	0.079	0.073	0.079
8	0.088	0.095	0.092	0.095	0.096	0.061
9	0.085	0.080	0.091	0.079	0.108	0.098

Where P(o) = observed proportion
P(c) = expected proportion based on Benford's law
Source: Researchers' Computation, (2022)

Graphical Representation of Second Digit Distribution

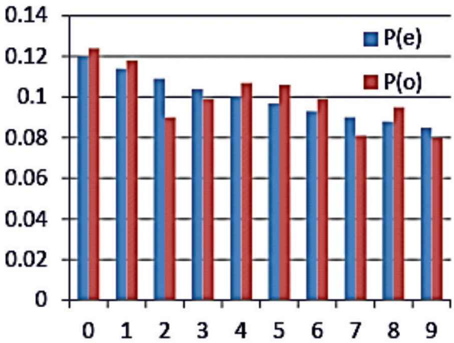

Fig. 6: s.d. Distribution 2003-2005

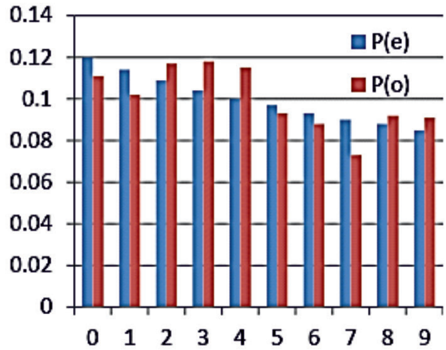

Fig. 7: s.d. Distribution 2006-2008

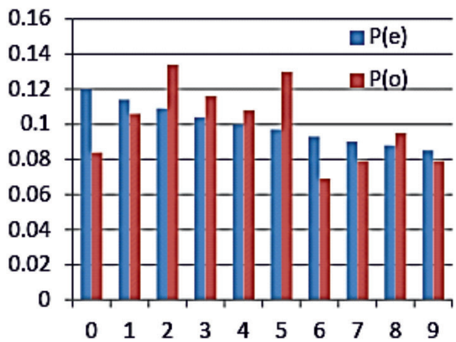

Fig. 8: s.d. Distribution 2012-2014

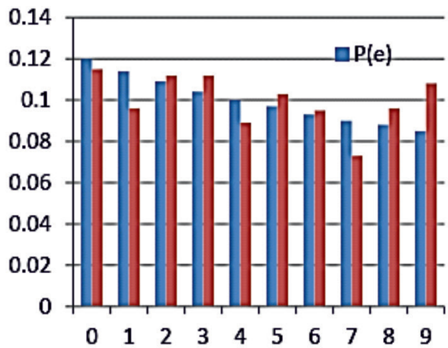

Fig. 9: s.d. Distribution 2015-2017

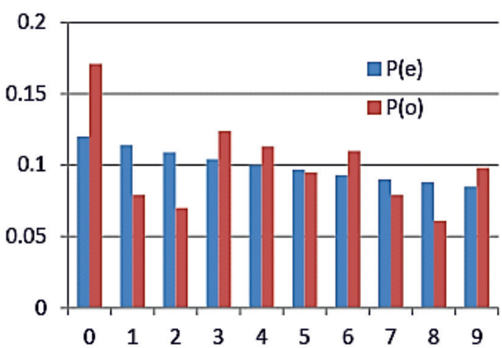

Fig. 10: s.d. Distribution 2018-2020

Table 4 and the graphical illustrations in figures 6–10 show the analysis of the first digits for the five clusters of years analyzed. Test results for all the clusters indicate a weak fit of the data to Benford's law. Further, the Table 4 shows a higher usage of digit 5 as the second digit than the expected according to Benford's law between 2003 and 2005 with a proportion difference of 0.009, and a lower than expected usage of 2 as the second digit with a proportion difference of 0.019, observable in the spikes seen in Figure 6 The usage proportion of other digits in the second place relatively conformed to the expected proportion according to Benford's law with minimal differences, as is clearly evident in Figure 6.

Analysis for the second cluster (2006–2008) presented in Table 4 showed a marginally acceptable conformity for digits 0, 2, 5, 6, 8, and 9 with proportional differences ranging between 0.04 and 0.09. However, there was a higher usage of digits 3 and 4 in the second place than expected according to Benford's law, with proportional differences of 0.014 and 0.015, respectively, which are obvious in Figure 7. Also, there was a lower than expected usage of digits 1 and 7, with proportional differences of 0.012 and 0.017, respectively.

Results of analysis for the third cluster (2012–2014) in Table 4 indicate a very poor fit of the second digits to Benford's law. Digits 1, 3, 4, 7, 8, and 9 had proportional differences between 0.008 and 0.012. Digits 2 and 5 occurred excessively when compared to Benford's expected frequency, with proportional differences of 0.025 and 0.033. Also, there was a lower than expected usage of digits 0 and 6, with proportional differences of 0.036 and 0.024, respectively. These variations in digits' proportion are vividly illustrated in Figure 8.

The fourth cluster (2015-2017) presented in Table 4 contained minimal variances between the observed and expected proportions according to Benford's law, particularly for digits 0, 2, 3, 4, 5, 6, and 8, which had proportion differences between 0.002 and 0.011. The usage of digit 9 in the second place was in excess of the expected frequency based on Benford's law with a proportion difference of 0.023. On the other hand, there was a lower than expected usage of digits 1 and 7, with proportional differences of 0.018 and 0.017, respectively. These variances are easily assessable in Figure 9.

The fifth cluster (2018–2020) presented in Table 4 contains the poorest fit of second digits to Benford's law, which is conspicuous in Figure 10. The digits with the closest conformity to Benford's law were 4, 5, 7, and 9, with proportional differences of 0.013, 0.002, 0.011, and 0.013, respectively. Digits 0, 3, and 6 had a very high deviation in excess of the expected proportion, with proportion differences of 0.051, 0.020, and 0.017, respectively.

On the other hand, there was a lower than expected usage of digits 1, 2, and 4, with proportional differences of 0.035, 0.039, and 0.027.

4.4. Data analysis and test of hypotheses

This section provides the analysis of the hypotheses formulated in the study as well as the implications based on the hypotheses of the study.

4.4.1. Test of hypothesis one

Hypothesis One: Accounting data in Nigeria does not significantly conform to the Benford's law.

Table 5: Z-score Computation for 2003- 2005 data (Errant Financial Statements)

Digit	*F(o)*	*P(o)*	*P(e)*	*P(o)-P(e)*	*S.D*	*Z Score*
1	468	0.357252	0.30103	0.056222	0.012674	4.436159
2	160	0.122137	0.17609126	0.053954	0.010524	5.126839
3	187	0.142748	0.12493874	0.017809	0.009135	1.949468
4	115	0.087786	0.09691001	0.009124	0.008174	1.116245
5	126	0.096183	0.07918125	0.017002	0.00746	2.278958
6	93	0.070992	0.06694679	0.004046	0.006905	0.585866
7	61	0.046565	0.05799195	0.011427	0.006458	1.769535
8	52	0.039695	0.05115252	0.011458	0.006087	1.882382
9	48	0.036641	0.04575749	0.009116	0.005773	1.579037
	1310	1	1			

Source: Researchers' Computation (2022)

Table 6: Z- Score Computation for 2002-2008 data (Compliant Financial Statements)

Digit	*F(o)*	*P(o)*	*P(e)*	*P(o)-P(e)*	*S.D*	*Z Score*
1	296	0.314	0.301	0.013	0.0149292	0.870778
2	144	0.153	0.176	0.023	0.0123946	1.855641
3	122	0.129	0.125	0.004	0.010764	0.37161
4	110	0.116	0.097	0.019	0.0096326	1.972467
5	57	0.06	0.079	0.019	0.0087792	2.164194
6	63	0.067	0.067	0	0.0081375	0
7	46	0.049	0.058	0.009	0.0076077	1.183012
8	54	0.057	0.051	0.006	0.0071603	0.837952
9	52	0.055	0.046	0.009	0.0068182	1.320004
	944	1	1			

Source: Researchers' Computation, (2022)

Table 7: Z-Score Computation for 2012-2014 data (Compliant Financial Statements)

Digit	*F(o)*	*P(o)*	*P(e)*	*P(o)-P(e)*	*S.D*	*Z Score*
1	231	0.345	0.301	0.044	0.017251	2.550589
2	141	0.2	0.176	0.024	0.014322	1.675718
3	84	0.105	0.125	0.02	0.012438	1.60798
4	59	0.079	0.097	0.018	0.011131	1.617158
5	56	0.079	0.079	0	0.010145	0
6	37	0.052	0.067	0.015	0.009403	1.595228
7	34	0.048	0.058	0.01	0.008791	1.137549
8	36	0.051	0.051	0	0.008274	0
9	29	0.041	0.046	0.005	0.007878	0.634639
	707	1	1			

Source: Researchers' Computation, (2022)

Table 8: Z-Score Computation for 2015-2017 data (Compliant Financial Statements)

Digit	*F(o)*	*P(o)*	*P(e)*	*P(o)-P(e)*	*S.D*	*Z Score*
1	338	0.313	0.301	0.012	0.013964	0.85935
2	169	0.157	0.176	0.019	0.011593	1.63887
3	122	0.113	0.125	0.012	0.010068	1.191881
4	109	0.101	0.097	0.004	0.00901	0.443957
5	95	0.088	0.079	0.009	0.008212	1.095998
6	83	0.077	0.067	0.01	0.007611	1.31381
7	66	0.061	0.058	0.003	0.007116	0.421592
8	43	0.04	0.051	0.011	0.006697	1.642424
9	54	0.05	0.046	0.004	0.006377	0.627217
	1079	1	1			

Source: Researchers' Computation, (2022)

Table 9: Z-Score Computation for 2018-2020 data (Compliant Financial Statements)

Digit	*F(o)*	*P(o)*	*P(e)*	*P(o)-P(e)*	*S.D*	*Z Score*
1	199	0.321	0.301	0.02	0.018407	1.086561
2	115	0.185	0.176	0.009	0.015282	0.588936
3	82	0.132	0.125	0.007	0.013271	0.527454
4	44	0.071	0.097	0.026	0.011876	2.18922
5	43	0.069	0.079	0.01	0.010824	0.923852
6	33	0.053	0.067	0.014	0.010033	1.39539
7	41	0.066	0.058	0.008	0.00938	0.852897
8	40	0.064	0.051	0.013	0.008828	1.472553
9	24	0.039	0.046	0.007	0.008406	0.832704
	621	1	1			

Source: Researchers' Computation, (2022)

Decision Rule: The decision rule is to reject the null hypothesis if the resulting z score is less than the critical value at the 5% significance level; otherwise, fail to reject the null hypothesis.

For the errant financial statements (2003–2005), digits 1, 2, and 5 failed the "digits' test," deviating significantly above the critical value of 1.96 with z-scores of 4.44, 5.13, and 2.28, respectively, at the 5% significance level. The other digits—3, 4, 6, 7, 8, and 9—passed the test with z-scores of 1.95, 1.12, 0.58, 1.77, 1.88, and 1.58, respectively. The data from 2006–2008 financial statements had digits 4 and 5 slightly above the critical value of 1.96 with z-scores of 1.97 and 2.16, respectively. The first digits of data obtained from 2012–2014, 2015–2017, and 2018–2020 passed the first digit test with z-scores all below the critical value of 1.96.

Hence, reject the null hypothesis and accept the alternate hypothesis, which implies that accounting data in Nigeria does significantly conform to Benford's law. 4.4.2 Test of Hypothesis Two Hypothesis Two: Benford's law is not significant in the detection of accounting fraud in Nigeria.

Table 10: Chi-square computation for 2003-2005 (Errant financial statements)

First Digit	*fo*	*fe*	*fo-fe*	*(fo-fe)^2*	*$\frac{\sum(fo-fe)^2}{Fe}$*
1	468	394	74	5476	13.898
2	160	231	-71	5041	21.823
3	187	164	23	529	3.226
4	115	127	-12	144	1.134
5	126	104	22	484	4.654
6	93	88	5	25	0.284
7	61	76	-15	225	2.961
8	52	67	-15	225	3.358
9	48	60	-12	144	2.4
	1310	1310			53.737

Calculated value of Chi-square = 36.814

Degree of freedom (df) = (r–1)

df = (9-1)

df = 8

Critical value at 5% significance level with 8 degrees of freedom is 15.51

Source: Researchers' Computation (2022)

Table 11: Chi-square computation for 2006-2008 (Compliant financial statements)

First Digit	*fo*	*fe*	*fo-fe*	*(fo-fe)²*	*∑(fo-fe)² / Fe*
1	296	284	12	144	0.507
2	144	166	-22	484	2.915
3	122	118	4	16	0.135
4	110	92	18	324	3.521
5	57	75	-18	324	4.32
6	63	63	0	0	0
7	46	55	-9	81	1.472
8	54	48	6	36	0.75
9	52	43	9	81	1.884
	944	944			15.504

Calculated value of Chi-square = 15.504Degree of freedom (df) = (r–1)
df = (9-1)
df = 8
Critical value at 5% significance level with 8 degrees of freedom is 15.51
Source: Researchers' Computation (2022)

Table 12: Chi-square computation for 2012-2014 (Compliant financial statements)

First Digit	*fo*	*fe*	*fo-fe*	*(fo-fe)²*	*∑(fo-fe)² / Fe*
1	231	212	19	361	1.703
2	141	125	16	256	2.048
3	84	89	-5	25	0.281
4	59	69	-10	100	1.499
5	56	56	0	0	0
6	37	47	-10	100	2.128
7	34	41	-7	49	1.195
8	36	36	0	0	0
9	29	32	-3	9	0.281
	707	707			9.085

Calculated value of Chi-square = 9.085
Degree of freedom (df) = (r–1)
df=(9-1)
df=8
Critical value at 5% significance level with 8 degrees of freedom is 15.51
Source: Researchers' Computation (2022)

Table 13: Chi-square computation for 2015-2017 (Compliant financial statements)

First Digit	*fo*	*fe*	*fo-fe*	*(fo-fe)²*	*∑(fo-fe)² / Fe*
1	338	325	13	169	0.52
2	169	190	-21	441	2.321
3	122	135	-13	169	1.252
4	109	105	4	16	0.176
5	95	85	10	100	1.681
6	83	72	11	121	0.143
7	66	63	3	9	2.618
8	43	55	-12	144	0.510
9	54	49	5	25	10.373
	1079	1079			

Calculated value of Chi-square = 10.373
Degree of freedom (df) = (r–1)
df=(9-1)
df=8
Critical value at 5% significance level with 8 degrees of freedom is 15.51
Source: Researchers' Computation (2022)

Table 14: Chi-square computation for 2018-2020 (Compliant financial statements)

First Digit	*fo*	*fe*	*fo-fe*	*(fo-fe)²*	*∑(fo-fe)² / Fe*
1	199	187	12	144	0.770
2	115	109	6	36	0.330
3	82	78	4	16	0.205
4	44	60	-16	256	4.267
5	43	49	-6	36	0.735
6	33	42	-9	81	1.929
7	41	36	5	25	0.694
8	40	32	8	64	2
9	24	28	-4	16	0.571
	621	621			11.501

Calculated value of Chi-square =11.501
Degree of freedom (df) = (r–1)
df=(9-1)
df=8
Critical value at 5% significance level with 8 degrees of freedom is 15.51
Source: Researchers' Computation (2022)

Decision Rule: The decision rule is to reject the null hypothesis and accept the alternative if the resulting X^2 value is less than the critical value at the 5% significance level; otherwise, fail to reject the null hypothesis. The errant financial statements (2003–2005) failed the test with a calculated X^2 value of 36.814, greater than the chi-square critical value of 15.51. The presumed compliant financial statements in 2006–2008, 2012–2014, 2015–2017, and 2018–2020 passed the test with calculated X^2 values of 15.504, 9.085; 10.373; and 11.501, respectively, all less than the chi-square critical value of 15.51.

Therefore, the null hypothesis that Benford's law is not significant in the detection of accounting fraud in Nigeria is rejected. This implies that Benford's law is significant in the detection of accounting data fraud.

4.5. Discussion of the Findings

From the analysis carried out above, accounting data conforms to Benford's distribution if it is free from misstatements or errors and analysed correctly.

Due to the earnings management that occurred between 2003 and 2007, Table 5 reveals a large departure from the expected first-digit proportions of the numbers 1, 2, and 5. Adjustments were made between 2006 and 2008 to address the implications of these misstatements, which led to modest variations from the anticipated first-digit proportion of digits 4 and 5, as shown in Table 6. The observed and expected first-digit proportions suit well in later years, demonstrating close agreement. This is consistent with Saville's (2006) research, which compared the financial statements of companies with poor reporting standards to those of organisations with high standards.

Findings also point to Benford's Law's efficiency in spotting irregularities in accounting data. Table 10's incorrect accounting data failed to pass the Benford's law test, showing that there were abnormalities in the data. Following years that were considered compliant passed the Benford's law, indicating that there were no data anomalies. This demonstrates the law's notable success in identifying accounting data fraud, which is similar to the findings of Egbunike and Amakor (2013), who looked at the law's effectiveness as a tool for fraud detection and prevention in business settings.

The investigation shows that Benford's law cannot definitively identify the types of abnormalities, fraud, or mistakes. The law is unable to identify the specific types of fraud or the suspicious goods in situations of fraud. Aside from fraud, which the law cannot catch, other reasons for variances could also exist. Similar to Table 11, where there were alterations but the data passed the test, modest adjustments that might be fraudulent might not be caught by this regulation. This supports Linville's (2008) research, which showed that Benford's law was ineffective at detecting the existence of questionable data unless the population's data percentage was high.

5. SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1. Summary of the findings

This study was conducted to assess Benford's Law's potential efficacy in identifying accounting data fraud in a Nigerian context. These conclusions are supported by the study's findings:

(i) Accounting data in Nigeria is one type of real-world data to which Benford's law can be applied.

(ii) Accounting data that has been altered by humans does not follow Benford's law, but accounting data that has been altered by humans does.

(iii) Because data with anomalies has a significant likelihood of failing the Benford's Law tests, whereas data without anomalies will pass the test, Benford's Law is useful in the detection of accounting data fraud.

(iv) The intrinsic limitations of Benford's law analysis prevent it from definitely detecting the sort of abnormalities, such as fraud or errors, their root causes, or the suspicious items.

5.2. Conclusion

The prevalence of accounting data fraud in Nigeria has increased recently, and the effectiveness of the fraud detection models in use is steadily declining as a result of the rising sophistication of those who commit the fraud.

Based on this, a study was conducted to examine the applicability of Benford's law to Nigerian accounting data, test the accounting data's conformance to Benford's law, and assess the possible efficacy of Benford's law in identifying accounting data fraud in the Nigerian context.

Findings from this study are consistent with those of other studies in that they show that Benford's law may be applied to accounting data; accurate or compliant financial data will follow Benford's distribution, whereas incorrect data would not. Anomalies in accounting data can also be found using the law.

5.3. Recommendations

The following recommendations are made based on the findings of the study:

i) Benford's law should be applied as an audit or forensic accounting tool for the detection of accounting data with misstatements.

ii) Benford's law should not be used as the only tool for accounting audits; rather, auditors should employ Benford's law as a complementary tool in conjunction with other audit techniques for enhanced effectiveness due to the inherent limitations of the law.

iii) Adequate test statistics should be used for measuring the goodness of fit to expected distributions such as Benford's law for more accurate results.

Acknowledgment

The authors appreciate the reviewers' comments and editorial assistance on this paper. This helped in improving the quality of the manuscript.

Conflict of Interest

There is no conflict of interest involved in the publication of this paper.

References

Abdullahi, R., & Mansor, N. (2015). Fraud triangle theory and fraud diamond theory; understanding the convergent and divergent for future research. *International Journal of Academic Research in Accounting, Finance and Management Sciences,* 5(4), pp. 38–45.

Albrecht, W., & Searcy, D. (2001). Top 10 reasons why fraud is increasing in the U.S. *Strategic Finance*, 82 (11), pp. 58–61.

American Institute of Certified Public Accountants (AICPA). (2002). *Statement on Auditing Standards (SAS) No. 99. Consideration of Fraud in a Financial Statement Audit*. New York: AICPA.

Amiram, D., Bozanic, Z., & Rouen, E. (2015). Financial statement errors: Evidence from the distributional properties of financial statement numbers. *Review of Accounting* Studies, 20(4), pp.1540-1593.

Asllani, A., & Naco, M. (2014). Using Berford's law for fraud detection in accounting practices. *Journal of Social Science Studies*, 1(2): pp.129-143.

Association of Certified Fraud Examiners (2012). *Report to the Nations on Occupational Fraud and Abuse:* 2012 Global Fraud Study. Austin, TX: ACFE.

Bakan. P. (1960). Response-tendencies in attempts to Generate Random Binary Series. *Journal of Psychology,* 73(1), pp. 127-131.

Beasley, M., Carcello, J., Hermanson, D., & Lapides, P. (2000). Fraudulent financial reporting: Consideration of industry traits and corporate governance mechanisms. *Accounting Horizons,*14(4), pp. 441–454.

Benford, F. (1938). The law of anomalous numbers. *Proceedings of the American Philosophical Society* ,78(4), pp. 551–572.

Brennan, N., & McGrath, M. (2007). Financial statement fraud: Some lessons from US and European case studies. *Australian Accounting Review*, 17(42), pp.49–61.

Burnaby, P., Howe, M., & Muehlmann, B. (2011). Detecting fraud in the organization: An internal audit perspective. *Journal of Forensic and Investigative Accounting,* 3(1), pp.195–233.

Carslaw, C., (1988). Anomalies in the income numbers: Evidence of goal oriented behavior. *The Accounting Review,* 63(2), pp. 321-327.

Carbarle, C. (2018). Using Benford's law to predict the risk of financial statement fraud in equity crowd funding offerings, *2018 Engaged management scholarship conference, Philadelphia, PA*.

Christian, N., Basri, Y., & Arafah, W. (2019). Analysis of fraud triangle, fraud diamond and fraud Pentagon theory to detecting corporate fraud in Indonesia. *The International Journal of Business Management and Technology,* 3(4), pp.1-6.

Cotton, D. (2002). *Fixing CPA Ethics can be an Inside Job*. Retrieved from: http://hdl.handle.net/10822/1006855 on 23rd July, 2021.

Cressey, D. (1953). *Other Peoples' Money. A Study in the Social Psychology of Embezzlement.* Montclair, Glencoe, USA: The Free Press.

Crowe, H. (2011).Why the fraud triangle is no longer enough. The effective use of Benford's Law to assist in detecting fraud in accounting data. *Journal of Forensic Accounting.* 1524-5586, pp.17-34.

Cunningham, E., & Bennett, D. (2021). Coronavirus burial pits in Iran so vast that they're visible from space. Washington Post. Available at: https//www.washingtorpost.com /graphics/2020/world/iran—cronavarius-outbreak grave. Accessed 11/10/2022.

Damla, U. S. (2022). *Benford's law: An empirical analysis of reported Covid-19 cases and institutional structures around the globe.* Univeristy Boccanir, Melono, B.Sc. Project in International Economic and Finance.

Egbunike, F., & Amakor, C. (2013). Fraud & auditors analytical procedure: A test of Benford's law. *EBS Journal of Management Sciences,* 1(1), pp. 14-31.

Elliott, R., & Willingham, J. (1980). *Management Fraud: Detection and Deterrence*. New York: Petrocelli Books.

Etim, E. O. (2013). Enhancing the quality of external audit. *African Journal of Contemporary issues,* 13(2), pp. 59 – 88.

Etim, E. O., & Ihenyen, C. J. (2013). Corporate reporting manoeuure effects and implications: A discourse. *Tropical Focus: The International Journal series on Tropical issues*, 14(1), pp. 154-166.

Etim, E. O., & Joseph, E. U. (2015). The impairment of audit functions: An assessment of some causes. Tropical Focus: *The International Journal series on Tropical issues,* 15(3), pp. 116 - 124

Etteridge, M., & Srivastava, R. (1999). Using digital analysis to enhance data integrity. *Issues in Accounting Education,* 14(4), pp. 675–690.

Farhadi, N. (2021). Can we rely on Covid 19 data? An assessment of data from over 200 countries worldwide. *Science Progress,* 104(2), pp. 73-91.

Grammaikos, R., & Papanikolaou, V. (2015). Applying Benford's Law to detect fraudulent practices in the banking industry. *Journal of Applied Finance and Banking Practices,* 13(2), pp. 117-133.

Gupta, R. (2013). *Analysis and Design of Data Mining Techniques for Prevention and Detection of Financial Frauds.* Doctoral Thesis, Maharshi Dayan and University.

Henselmann, K., Scherr, E., & Ditter, D. (2012). *Applying Benford's Law to Individual Financial Reports: An Empirical Investigation on the Basis of SEC XBRL Filings.* Working Papers in Accounting Valuation Auditing No. 2012-1, Friedrich-Alexander University Erlangen - Nuremberg. Retrieved from: http://hdl.handle.net/10419/88418on12thJuly, 2021.

Hill, T. (1995). A statistical derivation of the significant- digit law. *Statistical Science,*10(4), pp. 354–363.

Hussain, S. (2010). The Application of Benford's Law in Forensic Accounting: An Analysis of Credit Bureau Data. Available at SSRN: https://ssrn.com/abstract=1626696.

Intal, T., & Do, L. (2002). *Financial Statement Fraud: Recognition of Revenue and the Auditor's Responsibility for Detecting Financial Statement Fraud*. Master's Thesis, Göteborg University, Sweden.

Izedonmi, F., & Ibadin, P. (2012). Forensic accounting and financial crimes: Adopting the inference, relevance and logic solution approach. *African Research Review,* 6(4), pp.125–139.

Jones, M. (2011). *Creative Accounting, Fraud, and International Accounting Scandals.* Chichester, England: John Wiley and Sons Ltd.

Kassem, R. (2014). Detecting asset misappropriation: A framework for external auditors. *International Journal of Accounting Auditing and Performance Evaluation,* 10(1), pp.1–42.

Kilani, A. (2021a). Authoritarian regimes propensity to manipulate Covid-19 data: A statistical analysis using Benford's law. *Commonwealth & Comparative Politics,* 59(3), pp.319-333.

Kilani, A. (2021b). An interpretation of reported Covid-19 cases in post-Soviet state. *Journal of Public Health*, 43(2), pp. 409-410.

Kossovsky, A. (2006). *Towards a Better Understanding of the Leading Digits Phenomena.* Working paper, Hunter College, City University of New York.

Krakar, Z., & Žgela, M. (2009). Application of Benford's Law in payment systems auditing. *Journal of Indian Orthodontic Society (JIOS),* 33(1), pp.39-51.

Kumar, K., & Bhattacharya, S. (2003) Benford's Law and its application in financial fraud detection. *Advances in Financial Planning and Forecasting,* 11: pp.57–70.

Kwok, B. (2005). *Accounting Irregularities in Financial Statements.* Alders hot, Hants, England: Gower.

Linville, D. (2008). The problem of false negative results in the use of digit analysis. *The Journal of Applied Business Research, 24*(1), pp.17-26.

Montano, V. S., Sherylove, U., & Remolar, A. (2017). *Forensic Analytics of Financial Reports in Philippians Property Sector: The Benford's Law.* Munich Germany: Grin Verlag.

Muhsin, K., & Ahmad, N. (2018). What Determinants of Academic Fraud Behavior? From Fraud Triangle to Fraud Pentagon Perspective" Paper presented at the International Conference on Economics, Business and Economic Education 2018, *KnE Social Sciences*, pp.154–167.

Neuringer, A. (1986). Can people behave 'randomly'? The role of feedback. *Journal of Experimental Psychology,*115 (1), pp.62-75.

Newcomb, S. (1881). Note on the frequency of use of the different digits in natural numbers. *American Journal of Mathematics,* 4(1), pp. 39–40.

Nigrini, M. (1994). A taxpayer compliance application of Benford's law. *Journal of the American Taxation Association,*18(1), pp.72−91.

Nigrini, M. (1999). I've got your number. *Journal of Accountancy,1*87(5), pp.79-83.

Nigrini, M. (2012). *Benford's Law: Applications for Forensic Accounting, Auditing and Fraud Detection.* New Jersey: John Wiley and Sons, Inc.

Nigrini, M., & Mittermaier, L. (1997). The use of Benford's law as an aid in analytical procedures. Auditing: *A Journal of Practice and Theory*, 16(2), pp.52-67.

Onuorah, A., & Appah, E. (2012). Fraudulent activities and forensic accounting services of banks in Port Harcourt, Nigeria. *Asian Journal of Business Management,* 4(2), pp.124–129.

Ozevin, O., Yucel, R., & Oncu, M. A. (2020). Fraud detecting with Benford's law: An alternative approach with BDS and critical values. *Muhasebe Bilim Dunyasi Dergisi,* 22(1), pp. 107-126.

Pinkham, R. (1961). On the distribution of first significant digits. *The Annals of Mathematical Statistics,* 32(4), pp.1223–1230.

Puspasari, N. (2016). Fraud theory evolution and its relevance to fraud prevention in the village Government in Indonesia. *Asia Pacific Fraud Journal*, 1(2), pp. 177–188.

Radzinowicz , S., & Wolfgang C. (1997). *Crime and Justice. The Criminal Society of Nigeria.* New York: Basic Books Inc.,

Raimi, R. (1969). The peculiar distribution of first digits. Scientific American, 221 pp.109-119.

Raimi, R. (1976).The first digit problem. *The American Mathematical Monthly,* 83(7), pp. 521-538.

Sahiti, A., & Bektaslic, M. (2015). Detection techniques of fraud in accounting. *European Journal of Economic and Business Studies*, 1(2), pp. 96-110.

Saville, A. (2006). Using Benford's law to detect data error and fraud: An examination of companies listed on the Johannesburg Stock Exchange. *South African Journal of Economic and Management Sciences,* 9(3), pp. 341-354.

Silverstone, H., & Sheetz, M. (2007). *Forensic Accounting and Fraud Investigation for Non-Experts.* New Jersey: John Wiley & Sons Inc.

Smith, W. (2013). Lessons of the HealthSouth fraud: An insider's view. *Issues in Accounting Education,* 28(4), pp. 901–912.

Soltani, B. (2007).*Corporate Fraud, Corporate Scandals, and External Auditing: An International Approach.* Edinburgh: Pearson Education Limited.

Spathis, C. (2002). Detecting false financial statements using published data: Some evidence from Greece. *Managerial Auditing Journal,* 17(4), pp.179–191.

Stanley, B. (1994). *International Fraud.* New York; McGraw–Hill.

Talwar, S., & Mehta, K. (2015). Devising a model for accounting fraud detection based on Benford's Law. *IOSR Journal of Economics and Finance,* (IOSR-JEF), pp. 1–9.

Tammaru, M., & Alver, L. (2016). Application of Benford's Law for fraud Detection in Financial Statements: Theoretical Review. Paper presented at the 5th *International Conference on Accounting, Auditing, and Taxation,* (ICAAT 2016).

Unegbu, A., & Tasie, G. (2011). Identification of false financial statements: A pre-ante tool for investment decisions, solvency analysis and bankruptcy predictions. *African Journal of Business Management,* 5(10), pp.3813-3827.

Wallace, W. (2002). Assessing the quality of data used for benchmarking and decision making. *Journal of Government Financial Management*, 51(3), pp. 16-22.

Wells, J. (2017). *Corporate Fraud Handbook: Prevention and Detection* (5thEd.). Hoboken, New Jersey: John Wiley and Sons, Inc.

Wolfe, B., & Hermanson, D. (2004). The fraud diamond: Considering the four elements of fraud. *The CPA Journal*, 74(12), pp. 38–42.

Yin, H. (2016). *Financial Statement Conformance to Benford's Law and Audit Fees. (*Master's Thesis, Macquarie University, Sydney, Australia). Retrieved from:https://www.researchonline.mq.edu.au/vital/access/services/Download/mq:47060

Zack, G. (2013). *Financial Statement Fraud Strategies for Detection and Investigation.* Hoboken, New Jersey: John Wiley and Sons, Inc.

Zhou, W., & Kapoor, G. (2011). Detecting evolutionary financial statement fraud. *Decision Support Systems Journal,* 50(3), pp. 570-575.