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Detecting Accounting Anomalies Using Benford's Law: Evidence from the Malaysian Public Sector

Nooraslinda Abdul Aris^a, Rohana Othman^b, Muhamad Anas Mohd Bukhori^a, Siti Maznah Mohd Arif^a and Mohamad Affendi Abdul Malek^a

^aFaculty of Accountancy, Universiti Teknologi MARA

^bAccounting Research Institute

ABSTRACT

Fraud is an illegal activity that affects the organizations and the global economy at large. Surveys and reports by leading audit firms such as ACFE, Deloitte, KPMG and NFA have confirmed that the public sector is more vulnerable to fraud compared to the private sector. Comments in the Auditor General's (AG) Report 2012 concluded the same findings. Thus, with respect to fraud, detection, investigation, and preventive measures are extremely important. While anomalies or red flags act as indicators for the auditor, management and other responsible parties to investigate whether there is real fraud, auditing and statistics remain as the two primary strategies for detecting fraud. Taking this perspective, Benford's Law is an advanced digital analysis useful in uncovering anomalies. This paper evaluates 500 accounting data from public sector agencies in Malaysia using the First-Digit, Second-Digit, First-TwoDigit, First-ThreeDigit and Last-TwoDigit tests. Results show that Benford's analysis is a credible analytical tool in identifying and detecting suspicious accounts for further scrutiny of fraud incidences in the public sector. This study represents an initial effort to derive a tool to monitor and detect potential fraud incidences or trends, thereby enabling organizations to curb tendencies toward fraud and thus pilot an initiative towards an effective management of fraud risk exposure.

Keyword: *Accounting Anomalies, Benford's Law, Fraud Risk, Public Sector, Statistical Analysis*

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INTRODUCTION

Fraud transcends borders and is a global phenomenon. As fraud involves deception and dishonesty, it could, therefore, behave as a virus scourge among entities, either business or administration. No industry or organization is immune to such a scourge. The consequences of fraud constitute both financial and non-financial as fraud impacts revenue, profit, branding, and reputation; which, in a business, can lead to a loss of market share, or ultimately complete collapse.

Thus far, no organizations have been able to screen themselves completely from fraud, be it from the private sector or the public sector. This is simply because such behavior or conduct by its nature can be difficult to detect. The incidence of fraud in the public and government agencies appears to be rising and this is a genuine cause for worry. This is supported by the findings from Deloitte & Touche, KPMG, National Fraud Authority (NFA), PwC, Zurich Municipal and the Accountant-General's reports from various countries. The findings show that fraud in the public sector is a real issue, with the majority of public sector leaders recognizing that major incident risks will increase over the next three years (Zurich Municipal, 2012; Said, Alam & Khalid, 2016).

Federal, State, and Local Governments as well as other Government Agencies play significant roles to deliver key services to the general public. National economies commonly have public expenditure as a significant component of the gross domestic product (GDP), expenditure that is mainly generated from public sector entities. It is therefore incumbent for accounting data taken from the ledgers, journals and spreadsheets that support a financial statement from the public sector agencies to be maintained properly with the use of appropriate systems. Ironically, given the current climate, public sector agencies are hard-pressed to reduce and justify their expenditure. The negative financial and reputational impact of any fraud affecting public sector bodies will be heightened since society is less tolerant towards this unethical behavior (Abd Aziz, Said & Alam, 2015). The organization must ensure continuous growth while keeping the public trust.

Fraud is often presaged by accounting anomalies. Within this context, Benford's Law as an advanced digital analysis technique, is commonly used to identify frauds involving insurance claims (Lu & Boritz, 2005); credit card frauds, money laundering, telecommunications, computer intrusion (Bolton & Hand, 2002); tax evasion, employee expense reports, invoices, accounts receivable, accounts payable and also fixed asset records. Conformity Test (da Silva & Carreira, 2013), or Test of Reasonableness (Nigrini, 2011), is employed to verify whether the analyzed data set follows Benford's Law. The most common tests are First-Digit, Second-Digit, First-Two-Digit and Last-Two-Digit tests (Durtschi, Hillison, & Pacini, 2004; Nigrini & Mittermaier, 1997). The First-Two-Digit test is more focused compared to the earlier tests. It primarily detects anomalous duplication of digits and possible biases in the data due to error, internal control structure (i.e. structure of approving authority), and/or psychological factors with respect to numbers. However, it is observed that previous studies use either one or two tests to identify and detect suspicious accounts, and most of them focus on First-Digit and/or Second-Digit tests only (Diekmann, 2007; Johnson & Weggenmann, 2013; Plaček, 2014; Shikano & Mack, 2011) a test against this distribution was used to identify fraudulent accounting data. This test is based on the supposition that first, second, third, and other digits in real data follow the Benford distribution while the digits in fabricated data do not. Is it possible to apply Benford tests to detect fabricated or falsified scientific data as well as fraudulent financial data? We approached this question in two ways. First, we examined the use of the Benford distribution as a standard by checking the frequencies of the nine possible first and ten possible second digits in published statistical estimates. Second, we conducted experiments in which subjects were asked to fabricate statistical estimates (regression coefficients). This study aims to employ five tests, namely the First-Digit, Second-Digit, First-Two-Digit, First-Three-Digit and Last-Two-Digit tests.

Although interest on Benford's Law and digital analysis in detecting financial fraud is growing, there is still limited research on its application and efficiency (Bhattacharya, Xu, & Kumar, 2011) there has been relatively little academic research to demonstrate its efficacy as a decision support tool in the context of an analytical review procedure pertaining to a financial audit. We conduct a numerical study using a genetically optimized artificial neural network. Building on an earlier work by others of a similar nature, we assess the benefits of Benford's law as a useful classifier in segregating

naturally occurring (i.e. non-concocted. Johnson and Weggenmann (2013) demonstrated the effectiveness of Benford's Law in detecting data bias in smaller data sets from the US state governments. They used 450 summary financial data instead of actual accounting data that restricted the analysis to a macro level. Plaček (2014) on the other hand, applies Benford's Law in detecting data manipulation in the Czech Republic's governmental macroeconomic data. He tested the 2013 data using the First- and Second-Digit tests. The z-stats showed significant deviation and he believed it was due to the economic structural shift instead of a poor quality of data. This study extended on this with the First-Two-Digit, First-Three-Digit and Last-Two-Digit tests.

This paper is structured as follows: Section 2 reviews the literature on fraud in the public sector setting and fraud detection using Benford's Law. Section 3 discusses research method and data collection. Section 4 presents discussions of findings while the last section concludes the paper.

LITERATURE REVIEW

Definition, Classification and Cost of Fraud

Unlike an error or mistake, fraud is deliberate, intentional, and more often than not, involves the purposeful concealment of facts. As suspicious activities, fraud embodies an intentional act of misleading or committing harm, ultimately to others, with the aim of securing an unfair or unlawful advantage (Albrecht and Albrecht, 2004; Hopwood, Leiner & Young, 2008; Rezaee, 2010). Fraud involves misconduct elements such as deception (Grabosky & Duffield, 2001) and dishonesty (Singh, 2011), and typically alludes to the senior management, along with other attributes such as intent, desire, risk of getting apprehended, breach of trust, rationalization, etc. (Ramamoorti, 2008). Fraud may include trickery and employing cunning and unfair means by which the victim is cheated (Albrecht & Albrecht, 2004). It can also be committed in a variety of different ways, such as through mail, wire, phone, and the Internet, thus often making it undetectable. Fraudsters are prone to commit fraud probably as a means to fulfill their wishes for luxurious and extravagant lifestyles (Grabosky & Duffield, 2001; Nia & Said, 2015; Mustafa, Bakri, Mohamed & Said, 2017). Given the current

state where no industry is immune to fraudulent situations and the negative publicity that swirls around them, prevention and detection of fraud has become a major concern of many organizations.

Many classifications of fraud have been developed. However, the most common fraud classifications are corruption, asset misappropriation, and fraudulent financial reporting (ACFE, 2010; Rezaee, 2010; KPMG Australia, 2012; Kranacher, 2010). Table 1 below summarizes the trends of fraud from 2006 until 2014 obtained from a Global Fraud Study conducted by the ACFE and published in their Report to the Nations on Occupational Fraud and Abuse. The report is based on the results of an online survey opened to 34,615 Certified Fraud Examiners (CFEs) globally. The report gives an overall global picture of fraud and abuse without highlighting specific countries. The table shows although reported cases of asset misappropriation are high, the highest median losses are incurred by fraudulent financial reporting.

**Table 1: Frequency and Median Loss from Fraud
by Classification from year 2006 to 2014**

	Asset Misappropriation		Corruption		Fraudulent Financial Reporting	
	Frequency (%)	Median Loss (USD '000)	Frequency (%)	Median Loss (USD '000)	Frequency (%)	Median Loss (USD '000)
2006	91.5	150	30.8	538	10.6	2,000
2008	88.7	150	27.4	375	10.3	2,000
2010	86.3	135	32.8	250	4.8	4,100
2012	86.7	120	33.4	250	7.6	1,000
2014	85.4	130	36.8	200	9.0	1,000

(Sources: ACFE - Report to the Nation on Occupational Fraud and Abuse, Global Fraud Study 2006, 2008, 2010, 2012, 2014)

Globally, 34 percent of respondents surveyed reported that they had been victims of fraud in the form of economic crimes (PwC, 2011b). Gee, Button and Brooks (2010) found that the cost of fraud was previously measured inaccurately as data from both the private and public sectors were difficult to compile. However, the scenario has changed over the last decade. Fraud occurrence in the United Kingdom is estimated at around £14 billion annually with almost half, i.e. £6 billion, due to fraud in the public sector (PwC, 2011b). The United Kingdom's National Fraud Authority Annual Fraud Indicator 2013 estimated fraud loss in the public sector to

be £20.6 billion. This estimated fraud loss comprised £2.6 billion in the central government, £2.1 billion among local governments, £14 billion lost through tax fraud and £1.9 billion lost via benefits and the tax credit system [NFA, Annual Fraud Indicator (AFI) 2013]. KPMG Australia (2012) indicated that fraud has cost respondents at least \$373 million over the last two years. While KPMG Malaysia (2013) reported that only 26 percent of the respondents could quantify the exact amount of fraud loss which totaled RM2.407 million. One can surmise the total loss would be much higher if the percentage of respondents quantifying fraud loss was higher. Reported fraud estimates have been characterized as representing the tip of an iceberg. Given the enormous scale of fraud, there must be appropriate and effective measures to tackle this issue.

Fraud in the Public Sector

Fraud in the public sector has not gained much attention from academics and policy-makers as opposed to other types of crimes (Doig & Levi, 2009). The ACFE (2012) in their Global Fraud Study ranked government and public administration second after the banking and financial services in terms of victimized organizations. PwC (2011a) reported that, in Australia, on average, government and state-owned enterprises experienced a higher incidence of fraud than listed private entities. Surprisingly, the common types of economic crimes faced by the public sector are similar i.e. assets misappropriation, financial statement fraud, and bribery and corruption.

Fraud in the public sector in Australia is reported to have increased to 46 percent in 2011 as opposed to 37 percent in 2009 making it among the top five targets for economic crimes (PwC, 2012). This proves that the public sector is viewed as an easy prey by white collar criminals, which resulted in increased number of fraud occurrences, in recent years. Fraud in the public sector directly or indirectly victimizes every citizen in the country when one considers that fraud is a whole-of-business issue, involving not just technology but people and processes. Public fund is involved which could instead be utilized to finance public programs, facilities, hospitals and infrastructure, among others. A key pre-condition in tackling fraud is the recognition that it is more prevalent than the current published figures indicate and incurs a significant loss of government revenue.

The public sector is faced with various types of fraudulent schemes, namely corruption, billing, skimming, reimbursement, payroll, and financial statement fraud (ACFE, 2012). Deloitte & Touche (2008) identified six types of fraud affecting the public sector: failure to adhere to the procurement procedure, collusion with external suppliers or creation of fictitious suppliers, abuse of expense policies, misuse of public assets for personal gain, misreporting of budgets to obtain funding, and overtime or contractor abuse. Fraud is perpetrated by people who find the criminal gain is worth greater than the risk of detection. The perpetrator can come from any level in the organization; from senior management whose authority makes him/her easier to override controls, to a contract worker facing personal financial pressure, and hence to overcharge for work done.

Fraudulent schemes often start small and become bigger as the perpetrator becomes bolder after escaping detection. Mazar, Amir, & Ariely (2008) and Kirchner (2010) reiterated people who have committed small indiscretions over time may gradually be tempted to commit acts that are considerably more unethical, transgressing previously acknowledged permission thresholds. Stimulating initiatives in tackling the economic downturn and cost saving plans were identified as an opportunity for the fraudster to engage in unethical behavior. On average, over two-thirds of the cases are committed by employees (PwC, 2012). The higher incidents of fraud perpetrated by internal parties signal the importance of preventative measure taken by public sector agencies. Proactive fraud prevention measures will help organizations identify weaknesses in their environment and reduce opportunities for internal fraud.

Among businesses and other organizations surveyed in Malaysia, 44 percent have been victims of economic crimes in the last 12 months prior to the survey (PwC, 2011b). The direct cost of economic crimes to an organization can be difficult to determine. But in general, Malaysian respondents reported direct losses have increased. Economic crimes were also cited to have incurred significant collateral damages including damaged employee morale, brand reputation as well as business relationships. The statistics on the types of frauds in Malaysia is inconsistent. PwC (2011b) in a study on the private sector reports the most common economic crimes involved thefts or asset misappropriations (83 percent) surpassing bribery and corruption (34 percent) and financial statement fraud (27 percent). Economic crime is most prevalent in large organizations.

KPMG Malaysia (2013) on the other hand points out that in the private sector, bribery and corruption (90 percent) is a major problem followed by general fraud (52 percent). The survey also shows that 42 percent of fraud incidents were within the range of MYR10,001 to MYR100,000. Surprisingly, 64 per cent of the respondents believed that paying bribes is common in Malaysia. Poor internal controls, lack of internal auditor skill, lack of fraud awareness and nature of business are identified as contributing factors to fraud incidents. Common motivating factors for such unethical behavior include greed and personal financial pressure.

The Malaysian Auditor General and specific reports of the Public Accounts Committee (PAC), among others have highlighted mismanagement of public funds by government agencies (Abu Bakar & Ismail, 2011). The AG report provides performance audit feedbacks to the Government and other stakeholders on the effective mobilization of public fund for the numerous government programs, projects and activities. The information includes planning, execution and monitoring in ensuring the desired outcomes are achieved. The AG report highlights many instances of poor management of programs or projects that lead to severe losses to the government as a result of extravagance, wastefulness as well as fraud. This indicates lower value being placed on public money, sometimes even involving unnecessary expenditure on the part of the government. These cases demonstrate accountability and integrity in the government structure is deficient thus incurring public criticisms.

Fraud Detection using Benford's Law

The numbers of fraud cases are shocking, with over one-third of all frauds detected indirectly by 'chance' (Jans, Lybaert, & Vanhoof, 2009). ACFE (2012) asserts that initially most frauds are detected through tips as compared to other methods. Subsequently in 2014, the ACFE reiterated tips remained as the main detection of fraud. Employees and customers are the two important sources of tips. The Kroll Global Fraud Report 2013 estimated that two thirds of the firms hit by fraud in 2012 cited an insider as the key perpetrator (Kroll, 2013). Other than that, it is believed that an increase in automation and the use of technology are helping in the fight against fraudsters (PwC, 2012).

Accounting anomalies often imply the presence of fraud as it includes irregularities in source documents, faulty journal entries, and inaccuracies in ledgers. To uncover a complex fraud, a thorough investigation of all possible scenarios is required. Thus, it is important to understand the various characteristics of an accounting system. Further, knowing and understanding the strategies that may be employed by an entity in detecting fraud is essential (Abdul Aris, Othman, Mohd Arif, Abdul Malek, & Omar, 2013). One of the techniques used is Benford's Law which is explained below.

Benford's Law

Benford's Law is a digital analysis technique that examines the frequency of the digits in the data. A mathematical tool that proposes a probability distribution for first, second and other digits of numbers in data sets, it describes the sizes of similar phenomena as long as the sizes span multiple orders of magnitude (Cleary & Thibodeau, 2005). The law postulates that numbers in sets of data with low first digits, such as 1, occur with more frequency than numbers with high first digits, like eight or nine. Valid, unchanged data, free of exceptional transactions, will follow the projected frequencies. The introduction of Benford's Law to the auditing and accounting literature have driven researchers since to use digital patterns to detect data anomalies.

The Benford's principle has been applied to different sets of financial data, to detect fraud in insurance claims, corporate income tax, employee expense reports, vendor invoices, accounts receivable, accounts payable and also fixed asset records. Benford's Law makes fraud detection possible when it is known that real data correspond to the Benford distribution (Bauer & Gross, 2011).

Audit software that incorporates Benford's Law enables the identification of fraud and other irregularities in accounts payable, income tax forms, claims payments and other disbursements. Applying Benford's Law to auditing elevates the process to a more complex form of digital analysis and affirmed level. It enables overall scrutiny of the account to check if the numbers are distributed according to convention.

In the accounting fraternity, Benford's Law application began to be conducted at the end of the 1980s to test the integrity or legitimacy of data.

Varian (1972) had initially suggested these procedures for social science data. In employing digital analysis to investigate earnings manipulation, two contemporary works are worthy of acknowledgement, namely Carlsaw (1988) and Thomas (1989). Carlsaw (1988) noticed earnings numbers from companies in New Zealand did not follow the expected distribution. More zeroes occupied the second digit position with fewer nines. This could possibly imply earnings would well have been rounded up. Thomas (1989) observed similar trends among firms in the United States. Nigrini (1996) extended Carlsaw's and Thomas' work on earning manipulation, combining it with Benford's Law to perform digital analysis in identifying tax evaders. Then, Nigrini and Mittermaier (1997) have outlined practical applications of digital analysis in testing sets of accounting numbers and case studies of training students. Subsequently, Drake and Nigrini (2000) extended the initiative by brilliantly detailing the use of Benford's Law for auditing and thereafter pioneering the application of Benford's Law to accounting in detecting fraud.

Data Analytical and Statistical Testing of Benford's Law

The success of Benford's analysis is dependent on the frequency of numbers forming a set or pattern. Hence, the data must be sufficiently large and the time frame sufficiently long to form a pattern. The Benford's tests can be analyzed under collective and individual statistic. Collective and individual statistics such as Chi-Square Test, Mean Absolute Deviation (MAD) and z-statistics are the most common statistical tests (Durtschi et al., 2004) used by researchers. The statistical test compares the frequencies of the actual data and the data predicted by Benford's Law. The magnitude of deviation reflects the level of conformity to Benford's Law. Substantial deviation might suggest the possibility of fraud or fabricated data (Hill, 1995). Nigrini (2011) added Kolmogorov-Smirnoff (K-S), Logarithmic and Mantissa Arc as alternatives to the statistical tests mentioned earlier.

Given the varieties of the statistical analysis, Durtschi et al. (2004) outlined two underlying conceptual consideration when deciding on the effectiveness of Benford's Law. First, the digital analysis becomes less effective as the level of contaminated entries vis-a-vis data size drops. Second, there are many instances reported in previous empirical studies identified as non-confirming yet do not contain fraud.

Notwithstanding, the effectiveness of each of the statistical analysis is discussed in detail by Nigrini (2011). Z-statistics analyze the significant level of individual digit while Chi-Square, K-S and MAD analyze the entire set of data. Nigrini (2011) notes that z-statistics, Chi-Square and K-S tests are limited from what is referred to as the excess power problem. Only small deviations are overlooked when the data become large. Nigrini suggests the data size should contain around 2500 to 5000 records if z-statistics, Chi-Square and K-S are employed.

The utilization of MAD to eliminate the effect of data size is recommended as MAD ignores the number of records. Unfortunately, MAD does not offer an objective and statistically valid cut-off scores. Concurrently, Drake and Nigrini (2000) offer guidelines on critical values based on the results of 25 diverse data sets shown in Table 2.

Table 2: Conclusion and MAD Range for the First Digit and First-Two Digit

Conclusion	MAD Range	
	First Digit	First-Two Digit
Close Conformity	0.000 to 0.006	0.000 to 0.012
Acceptable conformity	0.006 to 0.012	0.012 to 0.018
Marginally Acceptable Conformity	0.012 to 0.015	0.018 to 0.022
Non-Conformity	Above 0.015	Above 0.022

Source: www.nigrini.com/ForensicAnalytic and Nigrini, 2011

RESEARCH METHOD

The existence of the fraud triangle elements - pressure, opportunity, and rationalization will expose an organization to fraud. This study adopted statistical analysis by applying Benford's Law to assess the likelihood of fraud occurrence in the public sector setting (Nigrini, 2011).

Sample Size

This study presents a case study involving a Malaysian public Institute of Higher Learning comprising various faculties and non-academic administrative departments. Transaction data from the payment system in the years 2009 to 2010 were gathered where 500 accounting data were

randomly selected to check on the possibility of finding anomalies. Hill (1995), as cited in Durtschi, et al. (2004) noted most data on accounting conform to Benford Distribution and as such, can be subjected to digital analysis. Typical accounts comprise transactions that are outcomes of combining numbers. Data size is not a key factor since Benford analysis reveals peculiarities in an account. The data set includes information and description of voucher numbers, amount and issuance dates. The strict confidential policy practiced by the public sector disallows the revelation of the case study subject. The study begins with familiarization of various workflows and guidelines issued by the Ministry of Finance governing payments made to the supplier.

FINDINGS AND DISCUSSION

This section employs the five Digital Analysis Tests based on Benford's Law, which are First-Digit, Second-Digit, First-Two-Digit, First-Three-Digit and Last-Two-Digit.

First-Digit (1D) Test

First-Digit (1D) test examines the conformity of the data set following the distribution of first digit as suggested by Benford's Law. A close conformity implies the data follows Benford's distribution and subsequent Benford's test is applicable. The distribution of 1D test of the payment voucher is shown in Figure 1.

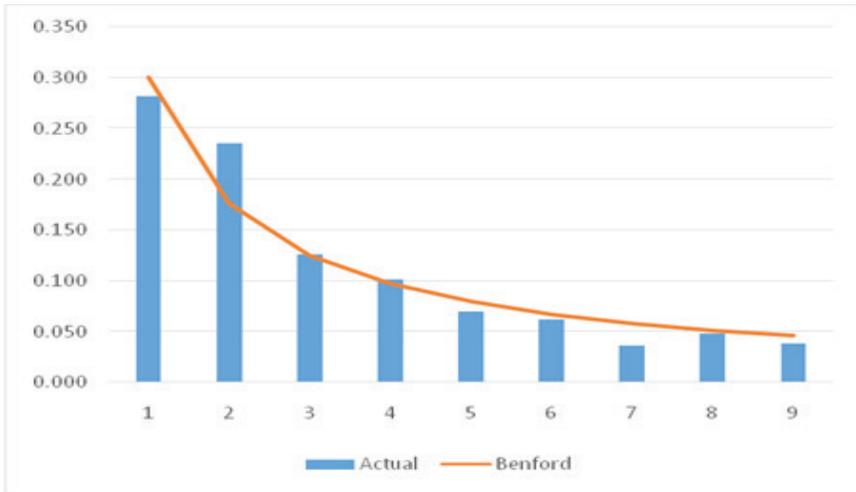


Figure 1: Proportion of 1D Test of 500 Payment Vouchers

Visually, Figure 1 shows that the data set follows Benford's Law where there is a steep slope from digit 1 to 4 vis-à-vis 5 to 9. It can be statistically tested using Chi-Square and K-S tests (Hill, 1995) and MAD (Nigrini & Mittermaier, 2001). This study employs MAD to analyze the magnitude of deviation or conformity to Benford's Law. The result of 1D test shows that the data marginally fits Benford's Law with MAD at 0.015 as shown in Table 3 below. All digits are below critical value ($z = 2.575$) except for digit "2". It will be impossible for the data set to fit Benford's Distribution perfectly. Hence, z-statistic is used to draw a significant line.

Table 3: MAD Conformity with Benford's Law

F1D Test						
Digit	Count	Actual	Benford's	Diff	Abs Diff	Z-Stat
1	141	0.282	0.301	-0.019	0.019	0.88
2	118	0.236	0.176	0.060	0.060	3.46
3	63	0.126	0.125	0.001	0.001	0.00
4	51	0.102	0.097	0.005	0.005	0.31
5	35	0.070	0.079	-0.009	0.009	0.68
6	31	0.062	0.067	-0.005	0.005	0.35
7	18	0.036	0.058	-0.022	0.022	2.01
8	24	0.048	0.051	-0.003	0.003	0.22
9	19	0.038	0.046	-0.008	0.008	0.72
Total	500	1.000	1.000	0.000		
				MAD	0.015	

Second-Digit (2D) Test

Similar to 1D test, Second-Digit (2D) test is conducted to test conformity to Benford's Distribution. Figure 2 shows the proportion of second digit of payment voucher against Benford's prediction.

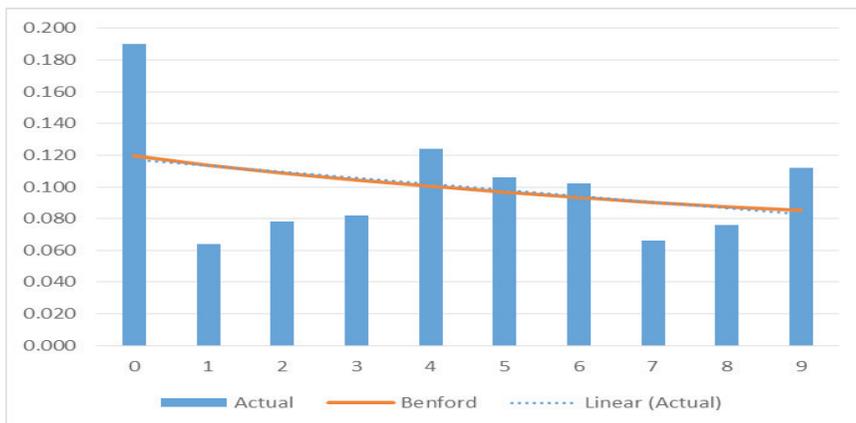


Figure 2: Proportion of 2D Test of 500 Payment Vouchers

The result shows that the data set does not have a smooth downward slope. Hence, a linear trend line was drawn to test whether or not negative slopes exist. Interestingly, the linear trend line is close to the Benford distribution. Hence, it is concluded that the 2D conforms to Benford's Law despite a high MAD of 0.028.

It is observed that there is a spike at number 0 and the scarcity of number 1 which may be a result of budget maximization, discount given by the supplier, payment of prefixed allowance rate, or procurement fraud. However, 2D test alone is not sufficient to point to the right direction. Hence, First-Two Digit (F2D), First-Three Digit (F3D), and Last-Two Digit (L2D) tests were conducted and the results are discussed below.

First-Two Digit (F2D) Test

First-Two-Digits (F2D) test shown in Figure 3 is employed to detect duplicate data and abnormal spike just below the internal threshold limit, which may be a result of fraud. Despite significant numbers of spike shown in the graph, the MAD score is low at 0.004 which implies that the whole data set closely conforms to Benford distribution based on the conclusion made by Drake and Nigrini (2000). However, individual assessment on the F2Ds using z-statistic highlights five F2Ds that exceed the critical value of 2.575 (Confidence Interval of 99%). The results are shown in Table 4.

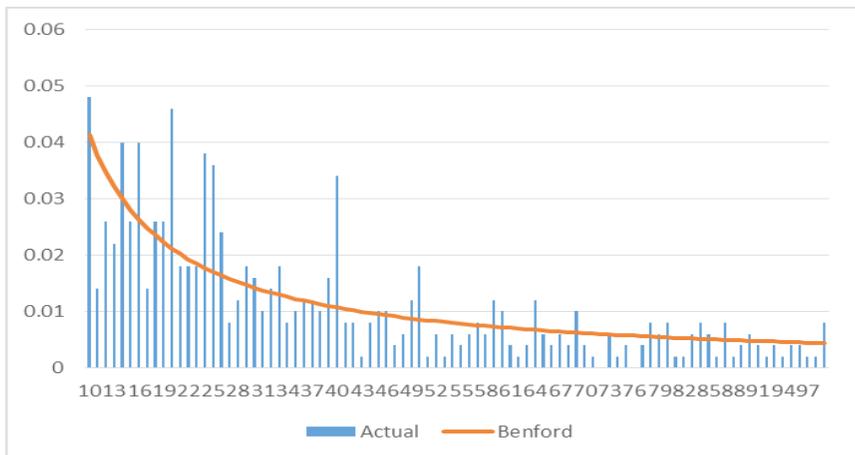


Figure 3: Proportion of F2D Test of 500 Payment Vouchers

The test identified five abnormal F2Ds which involve 53 records. Given the limited data available, researchers were not able to map the record against material description, staff and supplier information to assess the possibility of fraudulent pattern. As such, the record will be compared against the following test before being considered for further audit.

Table 4: Result of F2D Test

Digit	Actual		Benford		Z-Stat
	Count	%	Count	%	
40	17	0.034	5	0.011	4.836
20	23	0.046	11	0.021	3.697
24	19	0.038	9	0.018	3.265
25	18	0.036	9	0.017	3.105
11	7	0.014	19	0.038	2.672

In general, the government expenditure threshold is RM10,000.00, RM20,000.00, RM50,000.00, and RM200,000.00. Fraudsters may circumvent the higher approving authority by lowering the purchased amount just below the threshold. Should a fraudster employ this method to avoid detection, Benford result would show anomalies at digit “8”, “9”, “18”, “19”, “48”, and “49”. Analysis on F2D test result shows that there are no abnormal spikes below the internal threshold.

First-Three Digits (F3D) Test

The First-Three Digits (F3D) test was conducted solely to detect duplicate data that may arise from fraud. The result is shown in Figure 4. It is noted that Benford’s distribution moves towards normal distribution when placement value decreases or a combination of digit increases.

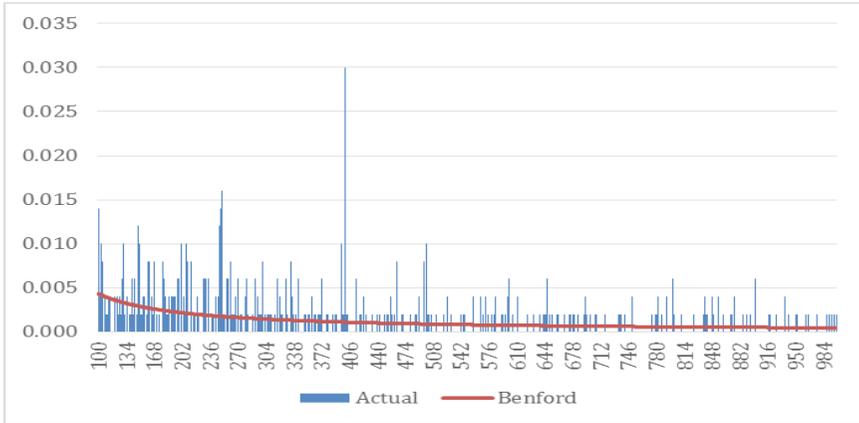


Figure 4: Proportion of F3D Test of 500 Payment Vouchers

The graph of F3D shows the data set contains many duplicate numbers and Table 5 provides the results of ten most deviated records.

Table 5: Ten Most Deviated Record Based on Z-Statistic Value in the F3D Test

Rank	Digit	Actual		Benford		Z-Stat
		Count	%	Count	%	
1	400	15	0.030	1	0.001	18.966
2	250	8	0.016	1	0.002	7.131
3	500	5	0.010	0	0.001	6.176
4	249	7	0.014	1	0.002	6.040
5	396	5	0.010	1	0.001	5.344
6	247	6	0.012	1	0.002	4.939
7	496	4	0.008	0	0.001	4.633
8	900	3	0.006	0	0.000	4.601
9	464	4	0.008	0	0.001	4.437
10	800	3	0.006	0	0.001	4.280
	Total	500	1.000	500	1.000	

F3D Test was conducted to analyze repeated digits in the data set. Since the F3D graph is moving towards normal distribution, using the

critical value of z-statistic as the cut-off point is no longer recommended. The test revealed 86 records which exceeded the critical value of z-statistic.

According to Nigrini (1994), seasoned fraudsters often get into the routine and in the end do not even try to invent authentic looking numbers. As a result, similar digit occurs more frequently compared to the natural digit.

Given the large amount of anomalies detected, only vouchers detected by F2D and F3D were selected for further analysis, i.e. F3D 400 and F3D 250. However, the above explanation is still insufficient to justify the significant existence of rounded digit. Further analysis is required to identify the relevant voucher for audit purposes.

Last-Two Digits (L2D) Test

The Last-Two Digits (L2D) test was performed to detect rounded decimal point and invented number. Benford's Law is moving towards uniform distribution as the researchers move from first digit to last digit. Hence, an assumption was made that each L2D are equally distributed (probability of occurrence = 0.01). Figure 5 shows the proportion of L2D in 500 payment vouchers.

Analysis on the data shows that 86 percent of the payment vouchers fall under the least controlled procurement method i.e., direct purchase from unregistered supplier. Most items purchased under this method are consumer goods. The payment vouchers issued for the purchase of low value items can also be identified as retail or consumer goods. These items fall under competitive market where psychological pricing is employed. Hence, we are expecting significant spikes at second digit "9" and last two digits "90", "95", and "99".

Interestingly, almost half of the data set has the last two digits "00". We also found that one-fifth of the data set contain second digit "0" causing a significant spike. The result suggests that the data contain significantly high intentionally rounded number.

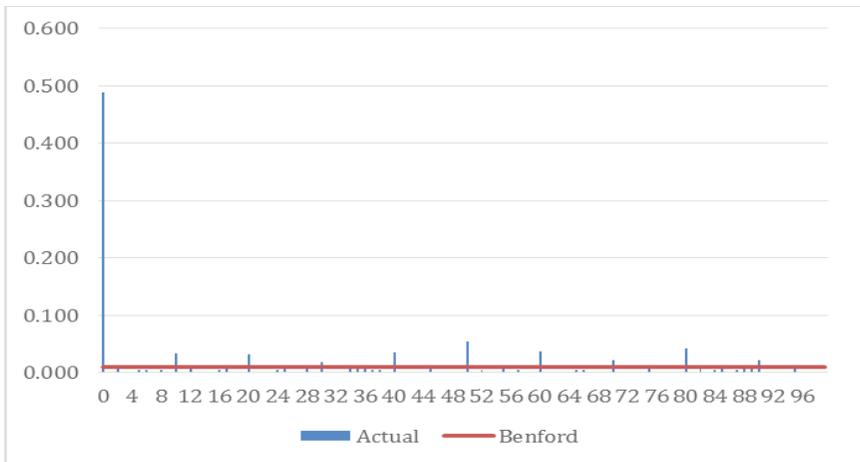


Figure 5: Proportion of Last-Two Digit of 500 Payment Vouchers

Discussion

The findings of this study cover three components – conformity, duplicate and rounded decimal. The 1D and 2D tests examined the data conformity to Benford’s distribution. The data analyzed satisfy the two tests which indicate it is suitable to apply Benford’s Law. This concurs with the findings by Burke and Kincanon (1991), Thomas (1989), Carshaw (1988), Sentance (1973), Wlodarski (1971), and Benford (1938) which assume that in many cases non-manipulated accounting data will follow a Benford set. The tests present a counter-intuitive but nevertheless easy-to-implement data mining technique where the primary objective is to examine the authenticity of a set of accounting data from an auditor or financial investigator’s perspective. A goodness-of-fit test with Benford’s law applied to an observed accounting data set cannot be considered conclusive, but it is one of several investigation tools that need to be utilized in detecting fraud (Kumar & Bhattacharya, 2007).

The second set, F2D and F3D tests were conducted to reveal any duplication. The findings indicate that there is duplication in the data set. Lastly, the L2D test was carried out to check on rounded decimal as a fraudster may not be too wise in violating numbers. The results suggest that there is a possibility of fraud since more than half of the data have “00” as the last digit, suggesting high intentionally rounded number. However,

limited access to the public data makes further analysis, interpretation and recommendation difficult. The best indication is suggesting further scrutiny on the data set.

As suggested by Busta and Weinberg (1998) analytical review procedures (ARP) may be used to improve the efficiency of audits as it compares expected relationships among data items to actually observed relationships using Benford's analysis. This deviation can indicate potential manipulation and can be used to signal the need for further audit testing. ARP produces two different signals, with four different outcomes. Signal 1 means more investigation is warranted. The first outcome is a correct signal if, in fact, the data being audited have been manipulated. Whereas the second outcome is an incorrect signal as the audited data maybe "clean" and does not require more audit effort. This normally resulted in Type I error. Signal 2 warrants for no further investigation. The third outcome is a correct signal if, in fact, the data being audited are "clean". The fourth outcome is an incorrect signal if, in fact, the underlying data being audited have been manipulated. This "undetected fraud," or "false negative" outcome is called a Type II Error. Undetected fraud may result in audit failure with substantial consequences. Combining ARP with Benford's Law enables real-life investigation of dubious financial fraud (Bhattacharya et al., 2011) there has been relatively little academic research to demonstrate its efficacy as a decision support tool in the context of an analytical review procedure pertaining to a financial audit. We conduct a numerical study using a genetically optimized artificial neural network. Building on an earlier work by others of a similar nature, we assess the benefits of Benford's law as a useful classifier in segregating naturally occurring (i.e. non-concocted.

CONCLUSION

This paper demonstrates the use of Benford's Law in detecting fraud as a prevention measure or to expand the premise for corrective actions. A sample of accounting data from the public sector was randomly analyzed to enlighten the readers. The findings conclude that Benford's analysis of accounting data is a useful tool in detecting potential fraud occurrence.

Accounting frauds typically encompass organizational and business scandals stemming from a lack of disclosure and /or control of the management. Such scandals represent the 'tip of the iceberg', akin to visible failure, which may be legal or quasi-legal. These scandals are typically investigated by appointed government agencies, external auditors and fraud examiners. With more cases being unearthed, there is a need for a tool to identify the warning signals of fraud.

There is increased awareness in the public sector that fraud may affect them; similar to the private sector. No organization in the world is immune from the fraud virus. The results from this study show that the accounts payables system may also be violated by the perpetrators to illicitly maximize their needs and wants. As mentioned earlier, the wish to live luxuriously and comfortably is one of the causal factors that increase the occurrence of fraud.

Statistical techniques have grown in terms of acceptance amongst users in identifying anomalies. This is proven with the outcomes of these statistical tests based on Benford's analysis which led the researchers to conclude that a proper application of the analysis potentially makes it a useful tool to identify suspect accounts for further scrutiny. Benford's analysis clearly is a credible analytical tool for auditors to detect fraud because it does not require aggregated data. Rather it is conducted on specific accounts using available accounting data. It can be very useful in identifying specific accounts for further analysis and investigation. It stands to reason that while such tests have many advantages, certain limitations must also be contemplated upon. Specifically, care must be exercised in interpreting the statistical results of the test to avoid any misleading conclusion. Benford's analysis should only be applied to accounts that conform to the Benford's Law distribution, and the auditors must be cognizant of the fact that certain types of frauds will not be found in this analysis.

In the final analysis, society is constantly in need of tools and techniques to boost surveillance, monitoring and identification of sinister acts perpetrated to take criminal advantage of current exposures and gaps. Audits have proven to be worthy of trusts and effectiveness to curb these mischiefs (Buang, 2008). However, the fraud activity would have been committed before it gets detected. Simply put, the damage has been done

followed by the reactive efforts to correct or curb the fraud and to absorb the destructive impact of the loss. Unfortunately, numerous fraud cases have culminated in closures or huge losses that has led to a complete shutdown of organizations, both public and private. It may then be prudent to adopt an outside-the-box approach by ‘nipping the bud’ off of the fraud tumor while still benign before further damage is done when it becomes malignant. This study can be seen to open up opportunities to uncover techniques to devise more effective efforts to curb the occurrence of fraud and to put a shackle on the unsavory stealth advantage currently exploited by fraud perpetrators. The application of analytical review procedures and establishing a forensic accounting department with the assistance of Benford’s Law may be seen as a viable vehicle in detecting fraud.

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