Jurnal Riset Akuntansi dan Keuangan 13(3) (2025) 583-598

Jurnal Riset Akuntansi dan Keuangan

Journal homepage: https://ejournal.upi.edu/index.php/JRAK/

Digital Forensics in Public Finance: Applying Benford's Law to Indonesian Government

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ABSTRACT

This study investigates the application of Benford's Law as a forensic tool to detect anomalies in the expenditure data of Indonesian government ministries and agencies. Utilizing transaction records from the SAKTI application for the year 2023, the research focuses on Goods & Services and Capital Expenditures. The analysis employs first-digit, first-two-digit, and first-three-digit tests to identify deviations from the expected digit distributions outlined by Benford's Law. While the first-digit test indicates general conformity, suggesting minimal anomalies, the first-two and first-three-digit tests reveal significant deviations, particularly around regulatory expenditure thresholds (e.g., Rp10 million, 50 million, and 200 million). These findings suggest potential structuring of transactions to circumvent stricter oversight, highlighting the need for enhanced auditing mechanisms. The study underscores the effectiveness of Benford's Law in forensic accounting within the public sector and advocates for its integration into routine audits to bolster financial transparency and accountability.

INFO ARTIKEL

Article History:
Submitted/Received 20 Oct 2025
First Revised 10 Nov 2025
Accepted 17 Nov 2025
First Available online 28 Nov 2025
Publication Date 13 Dec 2025

Keyword:
Benford Law, Compliance, Digital Forensics, Fraud, Public Finance

1. INTRODUCTION

Imagine a coin–with two distinct sides–being flipped: one displaying the denomination and the other presenting an image or symbol. In a single flip, there exists a 50% possibility of either side landing. Likewise, when rolling a die, each of the six faces has a probability of 1/6 of displaying the numbers 1 through 6. It is conceivable that the same probability pattern pertains to the numerical database (Damar et al., 2024; Özbaltan, 2024). Given a range of numbers from 0 to 9, there are 10 potential outcomes. Even when accounting for numbers of greater scales, such as tens, hundreds, even billions, we can still compute all combinations and their distributions. Nonetheless, this pattern does not apply to financial data. All financial operations, regardless of being revenue or spending, are not dictated by the frequency of nominal numbers. The large volume of financial transactions and their irregular distribution create opportunities for data manipulation (Annisa & Bakri, 2025).

The presence of abnormalities in number distribution is a significant challenge for identifying suspected manipulation (Shivram, 2024). Benford's Law is very relevant in this context. This concept was first proposed by Simon Newcomb (1881) and subsequently became well recognised as Newcomb-Benford's concept. Benford's Law demonstrates a distinctive distribution pattern in which the first digit of a numerical dataset has a particular uneven distribution (Gueron & Pellegrini, 2022a); for instance, the digit 1 occurs more often than the digit 9 as the first digit.

This methodology has been extensively used to discover abnormalities in diverse numerical datasets, including financial data, and has emerged as an excellent instrument for detecting probable fraud (Gueron & Pellegrini, 2022a; Melita & Miraglia, 2021a, 2021b). Benford's Law serves as a significant tool for spotting anomalous number distributions, hence facilitating the discovery of systemic fraud within the financial sector (Arezzo & Cerqueti, 2023; Arslan et al., 2024; Setyawan, 2020; Wang & Ma, 2024).

Similar to a hard-to-detect ailment, fraud has permeated several organisations throughout both the private and public sectors, posing significant obstacles to the reliability and accuracy of financial information (Cerqueti & Maggi, 2021; Pain & Ralchenko, 2024; Zago et al., 2023). Fraudulent conduct is often so organized that it is difficult for the organization's internal processes to identify. ACFE (2024) identified three types of fraudulent schemes, namely corruption, asset misappropriation, and financial statement fraud. Fraud significantly affects finances, resulting in income loss, performance decline, and simultaneously erodes investor confidence (Ben Hamida et al., 2024).

Due to its usefulness in fraud detection, the potential of Benford's Law should be utilized in government contexts. In Indonesia, where substantial budgets are managed across 48 ministries and agencies, detecting financial anomalies is critical to ensuring transparency and accountability. The Indonesian government has formulated a strategy to prevent and eliminate corruption (Rustiarini et al., 2019). Nonetheless, challenges persist, particularly with intersecting regulations, inadequate oversight and law enforcement, deficiency in integrity and professionalism among government personnel, and insufficient protection for whistleblowers and witnesses of corruption (Bakri et al., 2024; Bakri & Rahardyan, 2022; Lewis & Hendrawan, 2020; Masdar et al., 2021; Ratmono & Darsono, 2022).

DOI: https://doi.org/10.17509/jrak.v13i3.91881
p- ISSN 2338-1507 e- ISSN 2541-061X

Lewis & Hendrawan (2019) assert that corruption in Indonesia remains inadequately detected, complicating the regulation of service and financial flows required. Moreover, the danger remains exceedingly elevated, and investigations into fraud continued to be lengthy. According to the Corruption Perceptions Index (CPI) by Transparency International (2024), Indonesia scored 37, ranking 99th out of 180 countries. This indicates that the issue of corruption in Indonesia is consistently elevated, underscoring the need for new strategies to identify and mitigate possible fraud.

This research examines the utilization of Benford's Law in analysing Indonesian government expenditures. By comparing the actual digit distributions in the government expenditure transactions to the expected Benford's distribution, this study aims to identify deviations that may signal fraud risk. To achieve this, the study explores how Benford’s Law might serve as valuable instrument for fraud risk assessment, contributing to greater transparency and accountability in state financial management. Beyond theoretical implications, this study offers practical insights for strengthening governance and improving fraud detection mechanisms in Indonesia.

Benford’s Law

The Benford’s Law Test is categorized into primary tests, advanced tests, and associated tests. The primary tests, which form the foundation of Benford’s Law analysis, include the first digit, second digit, and first-two digit tests. Advanced tests, such as the summation test and the second-order test, can be conducted independently of the primary tests. Meanwhile, associated tests are supplementary and indirectly related to Benford’s Law, such as the number duplication test and the last-two digit test (Azevedo et al., 2021; Lacina et al., 2018).

First-Digit Test predicts the frequency of the leading digit in a dataset. For example, the digit 1 may appear as the leading digit in numbers like 10, 100, or 1,000 (Dang & Owens, 2020). This test provides a general overview of the dataset, measuring digit distribution, and can reveal manipulations or duplications when the observed frequency deviates from Benford’s predicted values. While it can sometimes show high compliance, datasets may exhibit patterns that differ due to processing. According to Szabo et al. (2023), the first-digit test is useful in detecting fraud when discrepancies are apparent.

The Second Digit Test evaluates the frequency of the second digit in a dataset. For instance, in the number 14,500, the second digit (4) is analysed. This test primarily determines if the data follows normalization behaviour, but its accuracy in detecting fraud is generally lower due to the common practice of data rounding in applied datasets (Herteliu et al., 2021). The First-Two Digit Test combines the first two digits for analysis, such as observing the digit combination 13 in the number 13,900. This test is more comprehensive and accurate for detecting fraud compared to the First Digit and Second Digit Tests. It can identify manipulation and deviations influenced by psychological or external factors and also detects abnormal digit duplication or potential data bias (Ben Hamida et al., 2024).

The First-Three Digit Test focuses on selecting audit samples and identifying unusual values caused by duplication (Ben Hamida et al., 2024). Compared to the First-Two Digit Test, it generates fewer samples for further examination (Gueron & Pellegrini, 2022b).

DOI: https://doi.org/10.17509/jrak.v13i3.91881
p- ISSN 2338-1507 e- ISSN 2541-061X

On the other hand, the Last-Two Digit Test is designed to identify fabricated or rounded numbers, making it particularly useful for smaller datasets (fewer than 10,000 entries). This test can easily detect rounded figures in reports, highlighting discrepancies that suggest such numbers may not represent actual values (Margellou & Pomonis, 2023).

Fraud

Fraud is defined by ACFE (2024) as an illegal act committed to achieve specific objectives. Similarly, Melita & Miraglia (2021a) describe fraud as an unlawful act characterized by deceit, concealment, or breach of trust. Cerqueti & Provenzano (2023) explain that fraudulent behaviour is driven by three factors, commonly referred to as the Fraud Triangle Theory. The first factor, pressure, arises from external demands such as lifestyle expectations, financial constraints, or family and workplace environments. The second factor, opportunity, is the perpetrator's perception of a chance to commit fraud without being caught. The third factor, rationalization, involves the perpetrator's justification of their actions, allowing them to perceive illegal behaviour as acceptable.

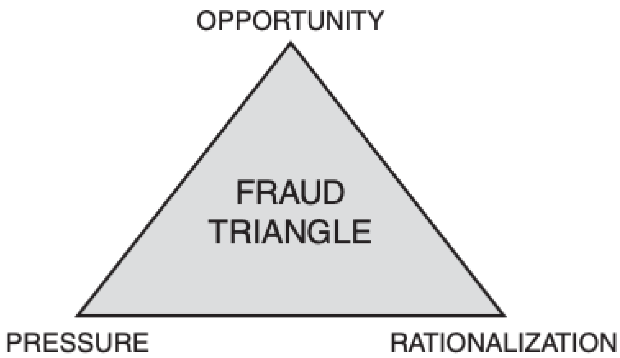

Figure 1. Fraud Triangle

ACFE (2024) categorizes fraud into three main types: asset misappropriation, fraudulent statements, and corruption as illustrated in Figure 2. Asset misappropriation can involve either the embezzlement of cash or the misuse of non-cash assets such as facilities. Fraudulent statements can take the form of financial or non-financial falsifications. Corruption encompasses conflicts of interest, bribery, illegal gratuities, and economic extortion (Marquart & Alan Thompson, 2024).

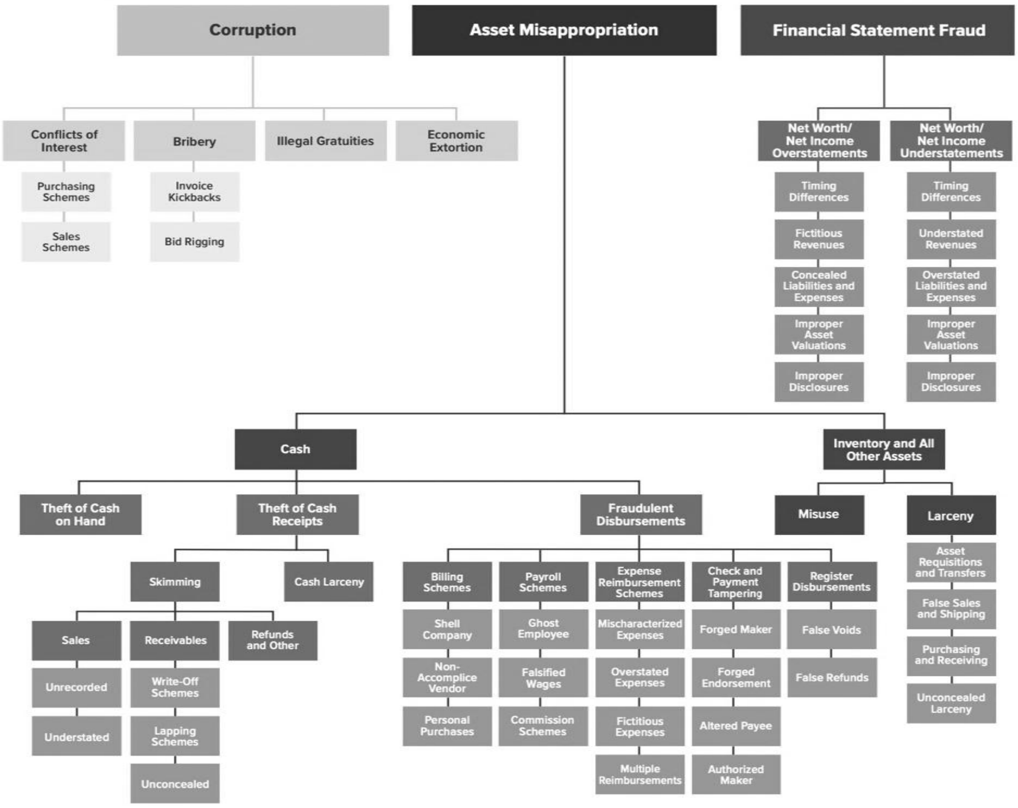

Figure 2. Fraud Diagram

2. METHODOLOGY

This study utilizes expenditure data from a ministries in Indonesia for the year 2023. The data was obtained from the SAKTI application, a state budget management application created by the Ministry of Finance of Indonesia. The data uses specific spending codes 52 and 53, namely Goods & Services Expenditure and Capital Expenditure. These two types of spending were chosen because they are reasonably frequent and relatively nominal compared to other types of spending. The data was subsequently processed using Active Data software to perform a Benford's Law analysis.

Table 1 shows how the data is distributed and divided into several strata. The strata are divided based on the level of potential fraud that is possible in each transaction range because there are different requirements. Transactions worth less than 10 million tend to have lighter requirements so that the disbursement process is more straightforward. At a maximum level of 200 million, each transaction needs to attach more documents. However, the procurement method for the procurement of goods and services can still be appointed directly according to the wishes of the Ministry holding the budgets.

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p- ISSN 2338-1507 e- ISSN 2541-061X

If it is more than 200 million, then the provider of goods and services cannot be appointed directly, so it must be carried out through an auction. This makes the process of nepotism in procurement more subdued. However, when the nominal transaction is more significant, the potential for loss if fraud occurs will also be more significant. Hence, it remains risky even though the requirements that need to be carried out are also stricter.

Table 1. Distribution of Expenditure Amount *(in Rp)*

Strata	Count	% of Count	Total Amount
0-10 million	10,494	21.04%	24,547,740,766
10-50 million	6,620	13.27%	172,900,624,454
50-100 million	3,794	7.61%	275,597,454,209
100-200 million	3,956	7.93%	576,693,652,289
200-500 million	5,156	10.34%	1,682,755,369,612
500 million-1 billion	3,689	7.39%	2,664,110,714,662
>1 billion	16,177	32.43%	4,567,512,209,348,970
Total	**49,886**	**100%**	**4,572,908,814,904,960**

Benford's Law examines the probability of the occurrence of specific digits using the following formula:

$$P(d) = log_{10}(1 + \frac{1}{d})$$

where *p* represents the probability of a particular digit, and *d* denotes the digit itself (1, 2, 3, ..., 9).

To validate this hypothesis, Nigrini (2012) conducted tests based on Z-statistics, chi-square x^2, and Mean Absolute Deviation (MAD). The first test, the Z-statistic, assesses whether the individual distribution significantly deviates from the expected distribution under Benford's Law. Mathematically, the Z-statistic is defined as follows.

$$Z = \frac{(|p - p_0|) - (\frac{1}{2n})}{\sqrt{\frac{P_0(1 - p_0)}{n}}}$$

If the Z-statistic exceeds the critical value, the null hypothesis is rejected at a 5% significance level. After examining individual distributions, the chi-square test x^2 is employed to evaluate the overall statistical significance of the observed distribution of transaction digit frequencies compared to the expected frequencies under Benford's Law. The formula for x^2 is as follows:

$$x^2 = \sum_{i=1}^{K} \frac{(P_i - P0_i)^2}{P_i}$$

If x^2 exceeds the critical value, the null hypothesis is rejected at a 5% significance level. The final test involves the MAD test, which evaluates whether the critical values align with Benford's Law. The MAD is calculated using the formula below, and its conclusion depends on the predefined range for each digit:

$$MAD = \frac{\sum_{i=1}^{K} |P_i - P0_i|}{K}$$

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3. RESULT AND DISCUSSION

Duplication Test Result

Before proceeding to Benford's Law Test, we also conducted a duplication test to provide an initial description of duplicated transactions. A duplicate test can also be a clue for auditors when conducting an audit of a transaction. Servers that continue to experience redundancy in certain numbers can actually describe a pattern that is being attempted by fraudsters. The need for robust auditing practices in government finance and operations cannot be overstated. Auditing serves as a fundamental mechanism to ensure the effective and transparent utilization of public funds, thereby fostering accountability, integrity, and public confidence (Edoumiekumo et al., 2020). One critical aspect of this auditing process is the identification of potential red flags, which can signal the presence of fraudulent activities or misappropriation of resources.

Table 2 shows the 30 highest recurring transactions in Ministries/Institutions in Indonesia. First, the duplicate transactions are small transactions with an average value of less than IDR 50 million. However, that is actually where the fraud is carried out. Transactions are broken down into certain amounts to avoid certain limitations so that fraudsters can carry out their actions. Transactions worth IDR 50 million and IDR 49 million have a duplication rate of 19 and 17 times, respectively.

These two amounts can be used to carry out fraud because the IDR 50 million limitation is the limit permitted by the Ministry of Finance of the Republic of Indonesia to use receipt evidence without other evidence. Procurement of goods and services in this amount is also relatively easy because procurement can be carried out directly without holding an auction. The combination of loopholes in the two regulations can be a clue for auditors to explore further through Benford's Law regarding the presence or absence of fraud in transactions with this amount.

Table 2. Duplication Test (in IDR)

Rank	Amount	Count	Rank	Amount	Count
1	217,260	47	16	3,000,000	24
2	5,500,000	45	17	2,000,000	23
3	289,680	45	17	1,800,000	23
4	540,000	43	19	80	23
5	144,840	32	20	185,000	22
6	72,420	32	21	370,000	20
7	17,500,000	31	22	50,000,000	19
8	5,000,000	29	23	30,000,000	19
9	579,360	29	24	21,875,000	19
10	362,100	28	25	651,780	19
11	1,500,000	27	26	320,360	19
12	1,080,000	26	27	15,000,000	18
13	434,520	26	28	10,000,000	18
14	3,250,000	25	29	1,303,560	18
15	11,000,000	24	30	49,000,000	17

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The duplication test, as a red flag identifier, has emerged as a valuable tool in the auditor's arsenal. This test aims to detect instances where transactions or payments have been duplicated, potentially indicating the diversion of funds or other irregularities. Effectively employing the duplication test can help internal auditors uncover potential instances of fraud or misuse of public resources, ultimately enhancing the overall governance and accountability of government entities (Mangala et al., 2017).

First-Digit Test

The analysis based on Benford's Law indicates that most of the first digits in the dataset follow the expected distribution, as shown in Table 3. Digits 1, 5, and 9 exhibit actual proportions slightly exceeding the proportions predicted by Benford's Law; for instance, digit 1 shows a difference of only 0.00119 from the expected proportion. The Z-statistics for these digits also indicate non-significant deviations, suggesting that these differences are minor and within acceptable bounds. The remaining digits (2, 3, 4, 6, 7, and 8) either match or fall below the expected Benford proportions, indicating no violations of the law.

Table 3. First-Digit Test

First Digit	Count	Proportion	Benford Proportion	Difference	Upper Bound	Lower Bound	Z Statistic
1	15,038	0.302	0.301	0.00119	0.305	0.296	0.174
2	8,592	0.172	0.176	0.00388	0.179	0.172	2.267
3	6,208	0.124	0.124	0.00051	0.127	0.122	0.340
4	4,685	0.093	0.096	0.00301	0.099	0.094	2.259
5	4,038	0.080	0.079	0.00175	0.081	0.076	1.435
6	3,307	0.066	0.066	0.00066	0.069	0.064	0.584
7	2,858	0.057	0.057	0.00071	0.060	0.055	0.667
8	2,552	0.051	0.051	0.0000	0.053	0.049	-0.006
9	2,350	0.047	0.045	0.0013	0.047	0.043	1.420
Total		**49,628**	**Mean Absolute Difference**		**0.0013616**		

Overall, the dataset demonstrates a strong alignment with Benford's Law. With a Mean Absolute Difference (MAD) of 0.00136, the dataset shows very minimal deviation from the expected distribution. Although there are slight over-representations for certain digits (1, 5, and 9), these differences are statistically insignificant. Consequently, there is no strong indication of manipulation or anomalies within the dataset based on this analysis.

Figure 3 visually confirms that the dataset closely adheres to Benford's Law, as the black bars (representing the observed first-digit proportions) align closely with the red line (representing Benford's expected proportions). Across all first digits, the observed proportions either match or closely follow the expected Benford proportions, with no significant deviations visible. Notably, the observed proportions for digits 1 and 2 are very close to the expected values, and subsequent digits show similar alignment. This consistency between the observed and expected distributions supports the conclusion that the dataset aligns well with Benford's Law, further validating the statistical results of the analysis.

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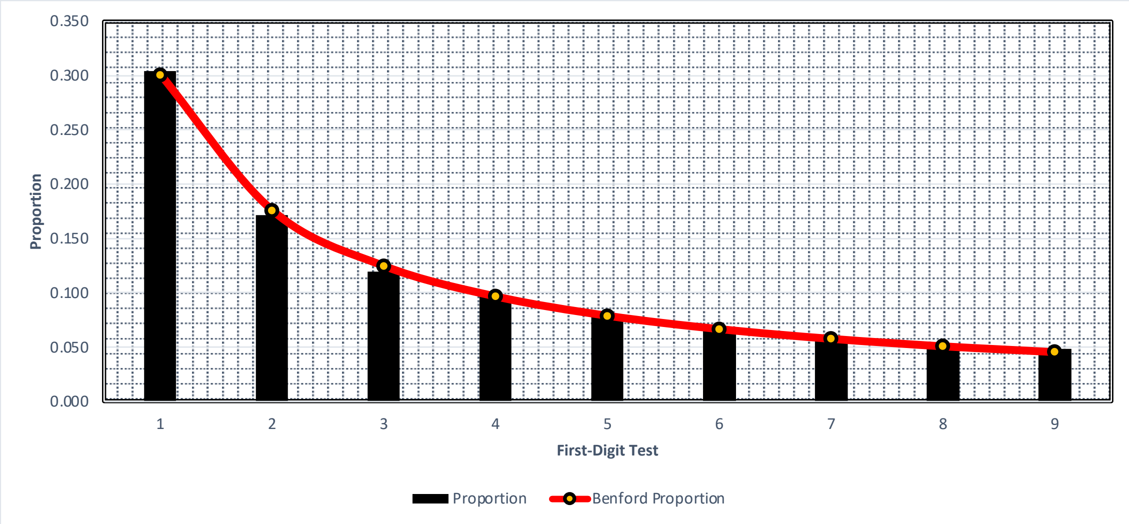

Figure 3. First-Digit Test

First-Two Digit Test

The results of first-two digit test reveal notable deviations from the expected proportions according to the Benford's Law. Among 90 numerical combinations, 43.33% (39 numbers) of them are classified as anomalies. The remaining 56.67% (51 combinations) conform to the Benford's Law, aligning with the proportionally distributed value with slight disparity, falling within the acceptable range.

Utilising the Z-statistic as the parameter in this dataset, combinations like 19, 50, 54, 72, and 99 show significant nonconformity. For example, combination of 50 has 0.01072 proportion value, exceeding 0.00212 point compared to the Benford's proportion (0.00860), making it as the combination with the largest proportion gap to the law. Furthermore, this combination also exposes the highest Z-statistic value of 5.09586.

Similarly, combinations of 54, 72, and 99 also show substantial deviations which surpass the expected values by substantial margins, by 0.00161, 0.00137, and 0.00119, with notable Z-statistics of 4.01156, 3.91173, and 3.97653, respectively, indicating substantial discrepancies. However, there is something interesting regarding the combination of 19, which appears 1,170 times in dataset, showing a proportion of 0.02345, slightly higher than the stated Benford's proportion (0.02228). While the Z-statistic of 1.75566 indicates a moderate-to-low deviation, its high frequency should be taken into consideration.

The over-representation of number 19 is not only alarming, but also suggest a possibility of a systemic factor influencing the dataset, such as data collection bias, or even potential data manipulation. Therefore, further investigation should be performed to delve into the root cause of this anomaly. Such initiative could help ensure data integrity and verify whether this pattern indicates a certain issue.

As shown in Figure 4, from a total of 49,614 data record of the 90 first-two digit combinations, it is visible that several combinations exhibit significant deviations, especially five combinations above, showing the bars peak transcending the Benford's red line. The significance of the dataset exceeding the expected proportion, along with certain combination with exceptionally high occurrence frequencies, indicates that the effectiveness

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of the Benford's Law test becomes more evident in the second condition assessment involving first two digits. Nevertheless, since the first-two digit test results show large fraction of nonconformities, further test with regulation compliance assessment, becomes necessary.

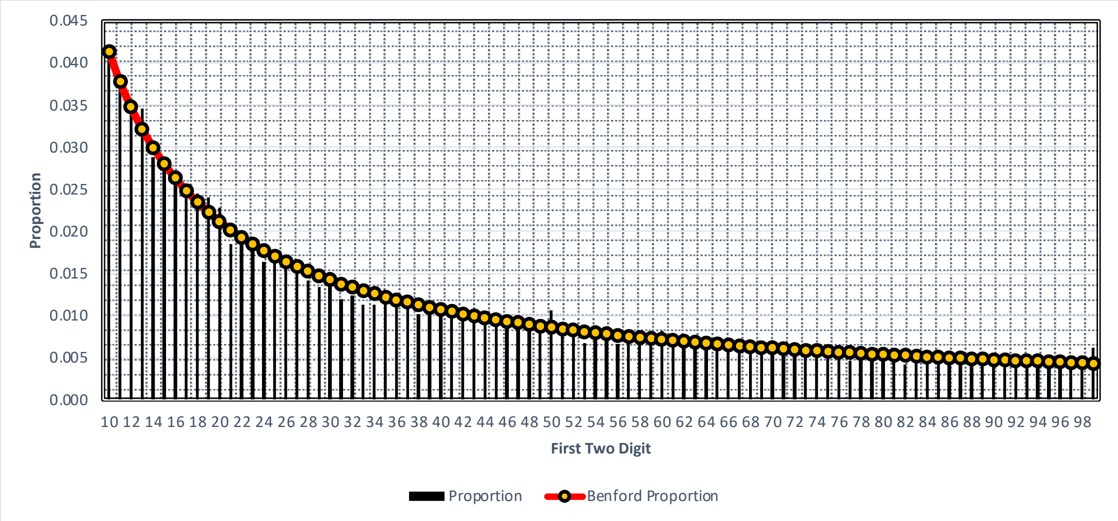

Figure 4. First-Two Digit Test

First-Three Digit Test

The first-three digit test results underline notable deviations from the Benford's Law expected proportions. Having all combinations tested, several three-digit numbers exhibit on-point oddities. Among 364 out of 900 entries, numbers like 100, 200, 450, and 500 stand out as the most significant anomalies, supported by the fact that the Z-statistics fell far above the acceptable confidence intervals. Amid the anomalies, 500 exhibits the most striking deviation, with a proportion of 0.0234 which surpasses the stated Benford proportion of 0.00087 by 0.00148. This is supported by a remarkably high Z-statistic of 11.07726, signalling a significant runaway from the calculated range. Likewise, 200 depicts a deviation of 0.00110 with a Z-statistic of 5.21584, while 450 and 100 depart with Z-statistics of 3.35910 and 2.57341 in respective manner.

The over-representation of these combinations hints potential abnormalities in the dataset. Specifically, the extraordinary Z-statistic of 11.07726 for 500 highlights a deviation far beyond natural variance, raising red flags about potential anomalies in data collection or manipulation. While smaller deviations, such as 100 (Z-statistics: 2.57341), might fall within the range of acceptable discrepancies, the value of deviations for 200, 450, and especially 500 cannot be overlooked. Once again, the systematic patterns observed above suggest that these anomalies may not be solely a coincidence, but rather an indication of systemic issues requiring immediate action.

As also shown in Figure 5, the imbalanced frequency of 500, for example, might indicate a human bias or intention in rounding to certain figures for purposes. Another example, number 200, which is also classified as excessive, might be also a sign of intended value concentration within obvious intervals. The aim is to avoid more rigid and complicated policies, both systematically and administratively, which could reduce the chance of organized fraud.

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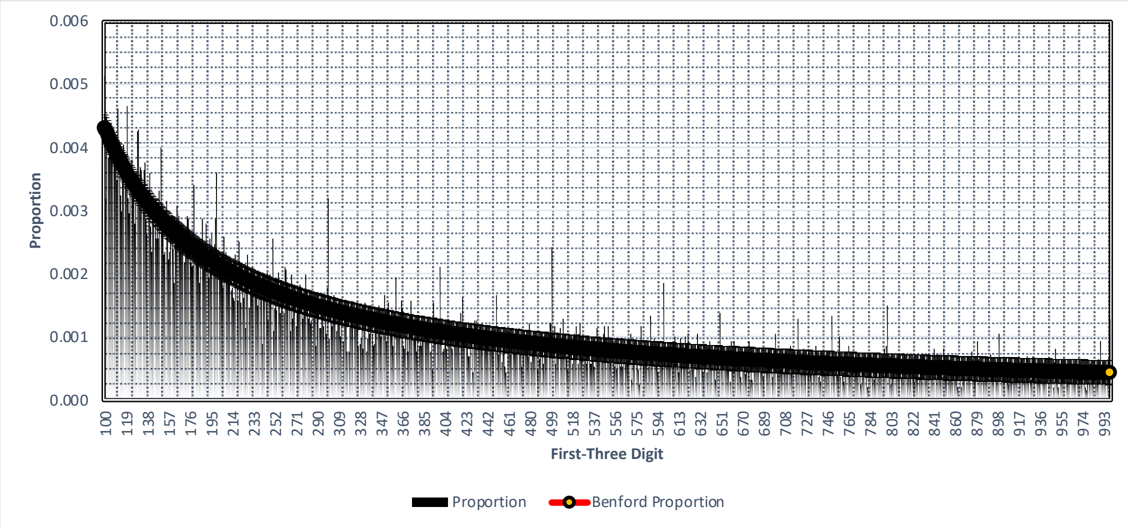
Figure 5. First-Three Digit Test



Discussion

The findings from the first digit test showcase a strong alignment between the dataset and the Benford's Law, as the overall distribution matches closely to the expected distributions. This indicates a relatively low tendency of anomalies or manipulations. However, even though statistically not substantial, the slightly higher representation of numbers 1, 5, and 9 needs closer scrutiny when contextualized within the implementation of Indonesia's regulation on government procurement of goods and services.

Appears in significant frequency and considerably complies the Benford proportion, the number 1 reflects the dominance of transactions beginning with this digit in the whole dataset. In Indonesia, government regulations set certain thresholds which determine the procurement procedures, expenditure approvals, and document requirements.

Considered as small-value and day-to-day transactions, IDR 10 million are mostly less subject to rigorous oversight, as it is also the maximum transaction limit for expenditures requiring only basic proof such as simple invoice, based on Indonesia's procurement regulation. However, its repetitive occurrence by 18 times, should trigger an investigation into possibility of any pattern or atypical intention.

Not only representing IDR 10 million, number 1 also signifies the occurrence of IDR 100 million transaction within the dataset, which corresponds to the upper limit for consultancy service conducted through direct procurement method. This threshold underscores the need for additional inspection to identify potential clustering of transactions near regulatory limits.

Similarly, the frequent occurrence of number 5 could be linked to expenditure patterns influenced by another regulatory thresholds. According to the same regulation, IDR 50 million set as the upper limit for any transaction which requires receipt for the accountability proof.

While the deviation from Benford's Law seems statistically immaterial, the frequent appearance of such values might suggest a tendency for transactions to array near this verge. This behaviour could indicate intended exploitation of the flexibility within the rules, although

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show compliance with administrative rules. On the other hand, number 9 describes a unique phenomenon. While its minor over-representation stands within acceptable statistical conditions, the probable interpretation lies in the strategic use of rounded values just below significant regulatory thresholds. For instance, expenditures nearing IDR 10 million and IDR 100 million, which has two distinct terms and conditions aforementioned, could be recorded as values starting with 9 (e.g. IDR 9 million, 9.9 million, 90 million, and IDR 99 million) to dodge provoking additional stricter requirements. Such tricks, while not explicitly fraudulent, could point to sophisticated manipulations designed to navigate regulatory constraints.

The results of the first-two digit analysis reveals that the combination of 99 stands out as a significant anomaly, exposing a higher likelihood of manipulation or irregularity. This appears when the Benford's Law applied to more specific kind of expenditure (code 52: expenditure on goods). The number likely represents IDR 9.9 million transactions, which are strategically placed right below the regulatory thresholds.

In accordance with the Indonesian government procurement regulations, IDR 10 million is a key limit. Expenditures up to this amount can bypass more extensive documentation requirements and are subject to minimal oversight. Although there is a possibility that this low-value expenses considered as a routine transaction such as subscription or maintenance, this may create a potential loophole for exploitation, as transactions clustered around this value (e.g. IDR 9.9 million) can occur with less scrutiny, leading to possible fraudulent activities such as fabricating invoices or inflating costs.

Given that 99 is observed frequently within the dataset, it may depict a pattern of rounding down transactions to just under regulatory limits. This practice is a quite common strategy to avoid additional documentation proof which require stricter verification and validation procedures. In other words, it will allow for flexibility in procurement practices without triggering more stringent controls which are required for larger expenditures.

While this condition does not necessarily lead to implicit fraud, the occurrence frequency of such number suggests a conscious and intended attempt to stay within regulatory limits. Further investigation needed to help determine whether these numbers indicate any misconduct procurement practices or still in acceptable operational boundaries.

Furthermore, an interesting pattern is obtained related to expenditures made by Ministries/Institutions in Indonesia from the results of the first-three digits. The spending is at a certain threshold for a provision that, if it exceeds the threshold number, triggers stricter requirements for making expenditures. These numbers include the first three digits: 100, 200, 450, and 500. The first four digits have a higher proportion than Benford and have a significant Z-statistic value.

The number 100 can refer to the equivalent of IDR 10 million, which represents the maximum limit for government expenditures that only require simple proof of payment in any form. This threshold is considered immaterial and, therefore, does not necessitate complex supporting documentation. Due to its simplicity, transactions with a nominal value of IDR 10 million are susceptible to fraud, as they can easily be accompanied by fabricated or inaccurate payment records. Duplicate testing supports this argument, revealing that transactions worth IDR 10 million occurred 18 times in the sample used in this study, making it one of the most frequently observed transaction values.

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Similarly, the numbers 450 and 500 may indicate similar situations, referring to transactions of IDR 45 million and IDR 50 million, respectively. The amount of IDR 50 million serves as the maximum threshold for transactions documented with receipts. Although receipts are more difficult to falsify than simpler forms of payment evidence, they remain susceptible to manipulation, unlike supporting documents required for transactions exceeding IDR 50 million. Transactions above this value must be signed by the relevant officials and undergo verification by the Ministry of Finance. Only upon validation by the Ministry can government ministries or agencies disburse amounts exceeding IDR 50 million.

The management of government expenditures is a critical aspect of public finance, as it not only shapes the allocation of resources but also plays a pivotal role in deterring fraudulent activities. Governments often impose specific limits on expenditures to maintain expenditure accountability and transparency, reducing the likelihood of dishonest practices (McGee et al., 2018).

The rationale behind the expenditure limits is that when government spending exceeds a certain threshold, the burden of proof for accountability becomes more substantial, making it more difficult to conceal fraudulent activities (Rustiarini et al., 2019). The complexity of the expenditure reporting and documentation requirements can serve as a deterrent, as it becomes increasingly challenging to hide the misappropriation of funds or other fraudulent practices.

Lastly, the number 200 presents a potential for larger-scale fraud, as IDR 200 million represents the maximum threshold for government ministries or agencies to directly appoint goods or service providers without requiring a tender process managed by the Ministry of Finance. This threshold allows direct appointments to be made for transactions up to IDR 200 million without a competitive bidding process.

Direct appointments may increase the risk of fraud due to potential off-contract agreements between procurement officials and the appointed goods or service providers. Such agreements could involve prearranged margins to be allocated to the procurement official, with the provider promised related projects in subsequent periods. This creates a mutually beneficial relationship between the two parties, fostering conditions conducive to fraudulent activities.

4. CONCLUSION

This study demonstrates the applicability of Benford’s Law in identifying anomalies within Indonesian government expenditure data, particularly in spending categorized under goods and capital expenditures. While the first-digit test results show strong conformity with Benford’s expected distribution—indicating limited evidence of manipulation—the first-two and first-three digit tests reveal notable deviations, especially around regulatory expenditure thresholds (e.g., IDR 10 million, 50 million, and 200 million). These deviations suggest potential structuring of transaction amounts to circumvent stricter oversight procedures. The findings emphasize that while aggregate data may appear compliant, more granular digit-level analysis uncovers patterns potentially linked to fraudulent behaviours or circumvention of regulatory controls.

The results highlight the need for enhanced fraud detection policies at the local government level in Indonesia. Regulatory frameworks should not only set nominal

DOI: https://doi.org/10.17509/jrak.v13i3.91881
p- ISSN 2338-1507 e- ISSN 2541-061X

transaction thresholds but also incorporate digital forensic tools like Benford's Law as part of internal audit routines. Specifically, automated alerts for overrepresented digit patterns near regulatory limits should be integrated into public financial management systems such as SAKTI. Furthermore, policies must mandate contextual audits for recurring rounded transactions just below key thresholds to deter systematic exploitation. By embedding statistical anomaly detection into procurement and disbursement monitoring, local governments can proactively safeguard fiscal integrity and strengthen public accountability.

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DOI: https://doi.org/10.17509/jrak.v13i3.91881
p- ISSN 2338-1507 e- ISSN 2541-061X