ORIGINAL SCIENTIFIC PAPER
UDK: 330.534.4(497.11)"2018/2022"
343.983:657.632
DOI: 10.5937/EKOPRE2506309A
Date of Receipt: May 17, 2025

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FORENSIC ANALYTICS OF FINAL ACCOUNTS OF THE REPUBLIC SERBIA[1]

Forenzička analitika završnog računa Republike Srbije

Abstract

In this paper, we will demonstrate that applying forensic tests to the data of the Final Accounts of the Republic of Serbia's budget reveals anomalies not included in the auditor general's and Fiscal Council's reports. We will use the tests of the high-profile review, Benford's law and the tests of the largest growth/decline of the subsets to test the correctness of the data of the final accounts of the budget of the Republic of Serbia. The reports from 2018 to 2022 will be analyzed to detect possible irregularities and errors in the final accounts, and a conclusion will be reached on the justification for applying these tests to the analyzed data.

Keywords: *national final accounts, forensic analytics, Benford's Low*

Sažetak

U ovom radu ćemo pokazati da se primenom forenzičkih testova na podatke Završnog računa budžeta Republike Srbije mogu otkriti anomalije koje nisu deo izveštaja generalnog revizora i Fiskalnog saveta. Koristićemo testove visokoprofilnog pregleda, Benfordovog zakona i testove najvećeg rasta/pada podskupova da bismo testirali ispravnost podataka završnog računa budžeta Republike Srbije. Izveštaji za pet izveštajnih godina, od 2018. do 2022. godine, biće analizirani kako bi se otkrile moguće nepravilnosti i greške u završnim računima i doneo zaključak o opravdanosti primene ovih testova na analizirane podatke.

Ključne reči: *nacionalni završni računi, forenzička analitika, Benfordov zakon*

1 Research conducted in the paper is part of the master thesis of Nađa Savić at the master program Forensic Accounting of the University of Belgrade - Faculty of Economics and Business

Introduction

They typically include the following: the Annual Budget Performance Report, the Income and Expenditure Account, the Public Debt Statement, the Balance Sheet of the Nation, the Consolidated Fund Statement, and the Auditor General's Report.

Budget accounting includes the conditions and methods of keeping business books, compiling, presenting, submitting, and publishing financial reports. The data contained in the Treasury's General Ledger are voluminous and impossible to see without analytical approaches and methods. The larger the volume of data, the more data quality problems, such as unwanted data, wrong data, and false data, and the need for big data to have high quality and reliability is becoming more pronounced.

The analysis will be carried out on the data for each year individually, as well as through comparisons across years, in order to monitor the movement of individual positions in the final accounts and to identify potential anomalies. The analysis will cover different data sets, as well as all positions of the final accounts combined, in order to properly assess the most suitable application of forensic tests.

A potential problem and inaccurate results may arise from the fact that the Final Account of the budget of the

Republic of Serbia is prepared only up to the fourth level of economic classification, which means that we will not have access to the classifications at the sixth level. Due to such a presentation of data, the data are aggregated in order to be presented at the fourth level of economic classification, then rounded to one thousand dinars and possibly corrected to fit into the figures at the third, second, and first levels of economic classification.

Forensic auditing refers to a branch of auditing that concentrates on uncovering and analyzing suspicious financial activities, fraudulent behavior, and violations involving money and assets [23]. In recent years, its importance has grown significantly across the corporate world, largely due to the increasing number of financial offenses worldwide [9].

The need for forensic audit services is on the rise, largely driven by the surge in dishonest and deceptive activities occurring within both corporate and public sectors worldwide [22]. As fraudulent schemes become more sophisticated and difficult to detect, forensic auditing has become an essential tool for uncovering the truth, gathering critical evidence, and aiding in the legal pursuit of wrongdoers.

With the expansion of businesses across international borders, forensic auditing has become increasingly vital in tackling financial wrongdoings that span multiple countries. Global companies must navigate a maze of different laws, regulations, and intricate networks of suppliers and partners, making them especially vulnerable to misconduct [27]. Forensic auditors serve as key defenders of financial integrity, helping organizations adhere to global compliance requirements and uncover questionable practices hidden in international dealings.

As the reach of commerce grows, so does the role of forensic auditing in reinforcing ethical standards, fostering openness, and ensuring stakeholders can rely on the accuracy and honesty of financial reporting worldwide.

When we refer to "forensic analytics of the national final account," we are essentially discussing the forensic examination of a country's financial statements — specifically the government's final accounts, including budget implementation, expenditures, revenues, and overall public financial management. This type of analysis typically focuses on detecting issues such as:

- Misappropriation of public funds
- Budgetary inconsistencies or fraud
- Ghost workers or fictitious projects
- Corruption or unauthorized transactions
- Public debt misreporting or irregular borrowing

Literature review

In forensic accounting, subset tests are used to detect fraud and financial irregularities. Mark Nigrini's book Forensic Analytics (Chapter 6) [14] is a foundational source, detailing how these tests uncover anomalies in financial data. There is a rich body of literature exploring how Benford's Law is used in auditing, especially for detecting anomalies and potential fraud in financial data. Here's an overview of key insights from the research.

Hill [4] provided formal mathematical proof of Benford's law and demonstrated how it actually works in stock market data and other accounting data. Durtschi et al. [2] provided empirical support for Benford's Law by showing near–perfect conformity in the first-digit distribution of their accounting data sample. Rauch et al. [19] extended this approach to macroeconomic series across European Union countries, uncovering especially strong deviations in Greece's figures.

Subsequent research (Van Caneghem [8], Saville [21], Sadaf [20], Nigrini & Miller [11], Nigrini [12], Joenssen [6], Alali & Romero [1]) has confirmed that most accounting datasets align closely with Benford's predicted pattern. However, Durtschi et al. [2] warn that digital analysis can produce false negatives when certain criteria aren't met. Benford testing is most reliable when the data are: generated by combining numerical values (for example, accounts receivable = units sold × price per unit); recorded at the transaction level (such as detailed expense logs); large in scale (ideally representing a full year of transactions); positively skewed (mean exceeds median). By contrast, Benford's Law offers little insight when applied to datasets composed primarily of invoices or checks, to sequences of assigned numbers, or to collections lacking true transactional records.

Mark Nigrini [13] outlines how Benford's Law can guide audit sampling by identifying transactions that deviate from expected digit patterns. However, he also cautions that this method can produce large samples and may not always be accurate—even when errors are seeded into the data.

Morales et al [10] in case study from Argentina applied Benford's Law to a state-owned enterprise's ERP system. They found that the law is effective for integrity testing, especially when analyzing large datasets (350+ tables). This approach helps internal auditors to flag suspicious areas without diving into every record.

Beyond First-Digit Tests, Wiryadinata et al [26] suggest combining Benford's Law with machine learning and multi-digit analysis (like first-two or last-two digits) to improve anomaly detection. Le at al [7] proposed a nine-step audit program that integrates Benford's Law with clustering techniques to distinguish between errors, benign anomalies, and fraud.

Methodology and dataset

In forensic accounting, subset tests are used to detect fraud and financial irregularities:

- *Largest Subsets Test*: Identifies small groups with unusually large totals, often used to spot collusion or kickback schemes.
- *Summation Test*: Aggregates values across subsets to detect outliers.
- *Growth Test*: Tracks changes in subset values over time to flag suspicious spikes or declines.

Benford's Law (commonly abbreviated as BL) refers to the phenomenon where, in many sets of numerical data—such as those found in mathematical tables, real-world measurements, or a mix of both—the leading significant digits do not appear with equal frequency, as one might intuitively assume. Instead, these digits tend to occur more frequently at the lower end of the scale. Specifically, BL states that in many datasets, significant digits follow a distinct logarithmic distribution. In its most widely recognized form, which focuses on the first significant digit in base-10 numbers, this pattern is also known as the First-Digit Phenomenon:

$$P(D_1 = d_1) = log_{10}\left(1+\frac{1}{d_1}\right) \tag{1}$$

where denotes the first significant decimal digit. For example, by formula (1) we have $P(D_1 = 1) = 0.301$, $P(D1 = 9) = 0.04575$, hence the probability of the digit 1 appearing is seven times greater than that of the digit 9. In a more comprehensive form than equation (1), Benford's Law describes the joint distribution of all decimal digits: for any positive integer m,

$$\begin{aligned} &P((D_1,D_2,\ldots,D_m) = (d_1,d_2,\ldots,d_m)) = \\ &= log_{10}\,(1 + (\Sigma^{m}_{j=1}\, 10^{m-j}d_j)^{-1}) \end{aligned} \tag{2}$$

is valid for all m-tuples $(d_1,d_2,\ldots,d_m)$, where d_1 is an integer from the set {1, 2, ..., 9}, and for all j ≥ 2, d_j is an integer from the set {0, 1, ..., 9}; in this context, D_2, D_3, D_4, and so on denote the second, third, fourth, etc., significant decimal digits, for example.

Most accounting datasets tend to follow a Benford distribution, which makes them well suited for digital examination (Hill [4]). This tendency arises because typical ledger figures are products of multiple combined values—for example, accounts receivable equals the quantity of goods sold multiplied by the unit price. Likewise, accounts payable and most revenue and expense categories generally conform to the same pattern.

Just as corporate accounting data often follows Benford's Law when untouched, macroeconomic figures from diverse sources and with varying distributions are also expected to conform. This expectation is supported by studies such as Nye and Moul [16], Gonzales-Garcia and Pastor [3], and Rauch et al. [19].

Nonetheless, caution is warranted when interpreting deviations from Benford's Law in any dataset. Such discrepancies should not automatically be taken as evidence of manipulation or poor quality; for instance, they may stem from structural changes within the data, as highlighted by Gonzales-Garcia and Pastor [3]. Still, any significant divergence should be treated as a potential warning signal—one that merits deeper examination and further analytical scrutiny.

The basic digit tests include evaluations of the first digit, the second digit, and the combination of the first two digits, collectively known as first-order tests. Among these, the first-digit test is the most widely discussed in both theoretical and practical contexts. However, this test operates at a broad level, limiting its practical value. Generally, poor alignment with Benford's Law suggests the presence of anomalies. In fraud detection, relying solely on the first-digit test can produce excessively large and inefficient audit samples. For example, examining all entries beginning with the digit 5 could require reviewing up to 10 percent of the entire dataset—a task that is impractical and resource-intensive. Any audit method requiring analysis of such a large portion of the data cannot be considered efficient or effective. For these reasons, we employ the first-two-digits test, as it offers a more targeted approach to identifying potential biases while generating a considerably smaller set of noteworthy items.

Several valid goodness-of-fit tests are available, many of which perform well with small datasets. In corporate and government contexts, however, datasets are typically large. One such test, the Z-statistic, assesses each of the 90 possible first-two-digit combinations individually. The results depend on both the magnitude of the deviation from Benford's Law and the total number of records (N). This test is affected by the "excess power" problem, where even minor deviations become statistically significant in very large samples. The chi-square test, on the other hand, evaluates the overall fit of the digit distribution as a whole. Like the Z-statistic, it becomes overly sensitive with large datasets, flagging minimal deviations as significant—limiting its practical usefulness.

The Mean Absolute Deviation (MAD) test avoids the sensitivity problem by not incorporating sample size (N) into its calculations. However, it lacks universally accepted critical thresholds. In the following subsection, we present a set of cut-off values proposed by Nigrini, along with their corresponding interpretations.

Given our decision to use the first-two-digits test for anomaly detection in accounting data, we now turn to the methods for measuring conformity. The Z-statistic is employed to determine whether the observed proportion of a particular first-two-digit combination significantly deviates from Benford's prediction. The calculation considers the absolute size of the deviation (i.e., the numerical "distance" between observed and expected values), the dataset size, and the expected proportion. The formula is presented in equation (3).

$$Z = \frac{|\mathrm{AP} - \mathrm{EP}| - \frac{1}{2N}}{\sqrt{\frac{EP(1-EP)}{N}}} \tag{3}$$

where *EP* represents the expected proportion, *AP* the actual proportion, and *N* the total number of records in the dataset. The term serves as a continuity correction and is applied only if it is smaller than the first term in the numerator, ensuring that the numerator remains positive. The Z-statistic are not suitable for assessing the overall level of nonconformity. To evaluate the combined behavior of the first-two digits, alternative tests such as the chi-square test, the Kolmogorov-Smirnov test, and the Mean Absolute Deviation test can be used.

The chi-square test is commonly applied to assess how well observed results align with expected values. In this context, the expected values correspond to Benford's proportions. The null hypothesis assumes that the first two digits in the dataset follow Benford's Law. The chi-square statistic for the first-two digits is computed as shown in Equation (4):

$$\chi^2 = \sum_{i=1}^{K} \frac{(AC - EC)^2}{EC} \tag{4}$$

Here, *AC* and *EC* refer to the Actual Count and Expected Count, respectively, while *K* denotes the total number of bins—90 in our case, corresponding to the 90 possible first-two digit combinations. The degrees of freedom for the test are calculated as *K – 1*, meaning the first-two digit test is evaluated with 89 degrees of freedom.

The Mean Absolute Deviation (MAD) test addresses the issue of excess power by disregarding the number of records, *N*. The MAD value is determined using Equation (5):

$$MAD = \frac{\Sigma_{i=1}^{K} |AP - EP|}{K} \tag{5}$$

where EP stands for the expected proportion, AP for the actual proportion, and K indicates the number of bins, which is 90 in the case of first-two digit analysis. The MAD is straightforward to interpret. The numerator measures the deviation between the actual and expected proportions for each first-two digit combination.

A set of critical values was established based on the analysis of 25 datasets same as the thresholds indicating close conformity and nonconformity are presented in [14].

The Final Account data to be used are publicly available on the websites of the National Assembly and the State Audit Institution.

Results

The Final Account of the Budget of the Republic of Serbia is subject to external audit by the State Audit Institution (SAI). In its analysis of the Final Account data, the SAI primarily relies on comparative methods—comparing data from the current year with those from the previous year, as well as comparing data presented in Form 5 – Budget Execution (which includes economic classifications from class 4 to class 9, [25]) against the Budget Law. Based on these comparisons, the SAI monitors deviations and requests clarifications from budget users regarding discrepancies.

By comparing our findings with those presented in the SAI reports, we can assess whether the anomalies identified by our forensic tests align with official audit observations—keeping in mind that the SAI has access to general ledger items that can be requested from the Treasury Administration.

We also consider the reports of the Fiscal Council to be highly relevant for analyzing our research results. The Council independently evaluates the credibility of fiscal policy in terms of compliance with established fiscal rules and thus promotes transparency and accountability in public finance management.

Since the Final Account forms are prepared at the fourth level of economic classification, it is not possible to conduct a detailed analysis of all economic classifications from the Treasury General Ledger at the sixth level. However, it is possible to identify classifications that warrant additional scrutiny. At the fourth level, all sixth-level classifications with the same first four digits are aggregated. Each of these fourth-level classifications is presented in thousands of dinars. During the preparation of the Final Account, certain rounding and adjustment procedures are necessary to align figures with the values reported at the third, second, and first levels of economic classification. These rounding and adjustment processes may have led to the classification of certain positions as problematic, even though such a classification may not reflect the actual situation. Therefore, this should be viewed as an initial analytical tool that highlights potentially questionable economic classifications and accounting entries.

The Final Account of the Budget of the Republic of Serbia is presented in the form of structured forms [24], which include data at the first, second, third, and fourth levels of economic classification. Considering the economic classifications from class 0 to class 9, the first level contains only 10 items, and the second level contains 37, which is considered insufficient for applying Initial High-Profile Screening Tests or Benford's Law conformity tests.

Therefore, our analysis focuses solely on data from the third and fourth levels of economic classification. Of the five Final Account forms, Form 1 represents the Balance Sheet, and Form 2 represents the Income Statement. The only two economic classes not covered by these forms are class 600000 – Expenditures for Repayment of Principal and Procurement of Financial Assets and class 900000 – Receipts from Borrowing and Sale of Financial Assets.

We analyze four data sets from each of the five Final Accounts from 2018 to 2022:

1. Data from all economic classifications at the third level;
2. Data from all economic classifications at the fourth level;
3. Data from Form 1 (Balance Sheet) at the fourth level;
4. Data from Form 2 (Income Statement) at the fourth level.

The selection of data sets for analysis was influenced by the volume of available data in each set.

Descriptive Statistics

Descriptive statistics serve to summarize the main characteristics of a dataset. While they are not a direct method for detecting anomalies, they play an important role in identifying extreme values, understanding the distribution shape, and defining data ranges.

Overview of Results:

Mean and Standard Deviation:

- The highest average values appear in the third-level classification datasets. While the mean slightly decreased in 2019, it increased significantly in 2020, mostly due to economic classification 015000 – Non-financial assets under preparation and advances, which grew from 1,424,005,000 RSD in 2018 to 13,846,035,000 RSD in 2022.
- The standard deviation follows a similar trend, with the largest spread observed in the third-level dataset, which again can be attributed to classification 015000.
- Minimum and Maximum Values:
- As expected, the minimum value is 0 across all datasets.
- The maximum values vary significantly. The highest observed maximums are within the third-level dataset, largely driven by classification 153000 – Transfers to mandatory social insurance organizations, with values exceeding 475 billion RSD.
- Skewness and Kurtosis:
- Skewness is highly positive in all datasets, indicating that most values are clustered at the lower end, with a few extreme high values—typical for financial and budget data.
- Kurtosis is also very high, particularly in the third-level dataset, again confirming the presence of heavy-tailed distributions and strong outliers.

These results align with expectations for financial data, where a small number of classifications typically account for a large share of total expenditures or revenues.

Benford's Law

During data preparation for conformance testing based on Benford's Law, all entries with values below 10 were removed, as recommended. The dataset was analyzed using the first-digit and first-two-digit tests, and conformity was evaluated using the Z-test, chi-square test, Kolmogorov–Smirnov (K–S) test, and the MAD test. The MAD test consistently indicated nonconformity for first-two-digit assessments and, in most cases, for first-digit analysis. Only in the firstdigit analysis of all fourth-level data for 2018 did the SAO test show acceptable conformity; in the firstdigit analysis of fourthlevel data for 2019, 2020, and 2022, as well as for the income statement in 2022, conformity was borderline acceptable. Consequently, in this context, the SAO test appears largely irrelevant.

Application of Benford's Law to 2018 Data

The application of Benford's Law to the 2018 dataset was conducted using various statistical tests to assess the conformity of digit distributions with theoretical expectations. At the third level of data aggregation, the Z-test revealed a statistically significant deviation for the leading digit "3," with a Z-value of 2.3449, exceeding the critical threshold of 1.96. Other digits remained within the expected range.

This anomaly was traced to several accounts, including: Account 122000 – Short-term receivables, Account 291000 – Passive accruals, Account 414000 – Employee social benefits, Account 485000 – Compensation for damage by government authorities, Account 513000 – Other real estate and equipment

Both the Chi-square and Kolmogorov-Smirnov tests confirmed overall conformity with Benford's Law. Due to the limited sample size (fewer than 300 entries), the first-two-digit test was not applied.

At the fourth data level, results indicated conformity with Benford's Law for the first digit. However, the first two digit test using the Z-statistic revealed anomalies at the digit pairs "49," "68," and "82." These correspond to 15 accounts, ranging from: Account 111800 – Loans to domestic private non-financial enterprises, to Account 921600 – Loan repayments from individuals and households in Serbia.

Balance Sheet data also showed conformity in the first-digit distribution. Again, due to the small sample size, the two-digit test was not applied.

For the Income Statement data, the Z-test flagged digit "8" as deviant (Z = 2.4718). This anomaly was linked to 15 accounts, starting with: Account 414200 – Educational benefits for employees' children, to Account 744100 – Voluntary current transfers from individuals and legal entities.

Despite the anomaly for digit "8," both the Chi-square and Kolmogorov-Smirnov tests affirmed general conformity.

There was limited alignment between the results across different data levels. Only Account 414000 (Employee Social Benefits) and its subaccount 414200 appeared consistently in both the third-level data and the Income Statement analysis. Alignment between the fourth-level data and Income Statement was found in the following accounts: Account21200 – Energy services, Account 713300 – Inheritance and gift taxes, Account 732300 – Current assistance from the EU.

These overlapping findings suggest that further scrutiny should be directed at accounts that appear anomalous across multiple datasets.

Comparison with the Republic of Serbia's 2018 Final Budget Account Law and the State Audit Institution (SAI) report revealed significant overlaps. Deviations in borrowing and sale of financial assets (~37%) and repayment and acquisition of financial assets (~29%) were also flagged in this Benford analysis. Specifically, Account 921600 – Loan repayments from individuals and households – appeared anomalous.

Other flagged accounts include: 732300 – EU current assistance, 744100 – Voluntary transfers (also above budget by ~12%), 442500 – Interest payments to foreign creditors (16% under budget), 461100 – Donations to foreign governments (nearly 5x planned), 463100 – Transfers to other levels of government (10% over plan), Capital expenditures: 512300, 512500, 513000, 522300 – all flagged.

SAI's audit reported discrepancies including incomplete recording of cash, securities, and domestic enterprise equity. Several of these matched Benford's anomalies (e.g., Accounts 122000, 732300, 744100).

The Fiscal Council noted higher-than-expected non-tax revenues due to one-time gains—reflected in class 73000 and 74000, which were also flagged. However, issues with accounts 111100 and 745100, noted in the audit, did not appear in the Benford results.

On the expenditure side, several anomalies noted by the Fiscal Council, particularly in the area of interest payments and transfers, matched our flagged accounts, including:441300 – Domestic interest payments, 442500 – Foreign interest payments, 463100 – Transfers to other levels of government, 461100 – Foreign donations, 472000 – Social protection.

Accounts related to guarantee payments (443000, 613000) were not flagged in this analysis.

The Benford analysis for 2018 highlighted a range of accounts whose digit patterns deviate significantly from expected distributions. Many of these correspond with findings in official reports, confirming the utility of Benford's Law as a complementary forensic auditing tool. Further investigation is warranted for overlapping anomalies across datasets.

Application of Benford's Law to 2019 Data

The analysis of all data at the third level of account classification indicated no significant anomalies with respect to the distribution of the first digit. This suggests a relatively high degree of conformity with Benford's Law at this level. Due to the dataset comprising fewer than 300 observations, the first-two digits test was not conducted for this level.

At the fourth level, however, a more granular analysis using the Z-test revealed anomalies in the distribution of the first-two digits, specifically for digit combinations 17, 48, 63, and 76. A total of 32 economic classifications were identified with amounts beginning with these digit pairs, ranging from account 014300 to 921300. This level of detail warrants further investigation as it may point to irregularities in specific transaction categories.

The Balance Sheet data was also subjected to Benford conformity testing. The distribution of the first digit in this dataset showed no statistically significant deviations, suggesting it adheres to the expected logarithmic distribution. Again, due to an insufficient sample size (fewer than 300 entries), the first-two digits test was not applied.

Likewise, the Income Statement data revealed no nonconformities in the distribution of first digits, and the dataset was not suitable for testing first-two digits for the same sample size reasons.

The Law on the Final Account of the Republic of Serbia for 2019 provides context for interpreting the statistical anomalies. In the section on the execution of the budget, deviations of approximately 13% from planned values were noted in the category "Expenditures for the repayment of principal and acquisition of financial assets" (account 496000). Interestingly, Benford analysis did not flag this account, which may indicate a limitation of the method in detecting moderate deviations if they follow expected digit distributions.

However, the Benford-based analysis did identify several anomalous accounts that correspond with significant budgetary deviations: Account 741200 – Dividends was flagged in the Benford test. This aligns with official findings that non-tax revenues and revenues from the sale of non-financial assets exceeded the plan, supporting the interpretation that this category merits scrutiny. Account 732400 – Capital transfers from the EU also showed deviations in the Benford test, consistent with the report's observation that donations deviated from the plan by nearly 4%. The analysis also highlighted account 612100 – Repayment of principal on securities (excluding shares) issued on foreign financial markets, and account 612300 – Repayment of principal to multilateral institutions as anomalies. This corresponds with the report noting higher than planned principal repayments. On the financing account, deviations in account 9121 – Receipts from the issuance of securities (excluding shares) on foreign financial markets were identified both in official reports and in the Benford analysis. Account 921300 – Receipts from repayment of loans to domestic public financial institutions, part of class 92 (receipts from sale of domestic financial assets), was flagged in Benford's test and was also shown to have exceeded the planned budget in the official report.

The State Audit Institution (SAI) report on the 2019 Final Account corroborates several of the findings revealed through Benford's analysis. The report notes that certain revenue categories were misclassified and that receipts from program and project loans were not recorded in the Treasury's General Ledger or disclosed as current-period income under classification group 912 – Foreign borrowing receipts. Many of these classifications were among those flagged by the Benford analysis, suggesting the method was effective in pointing to real accounting irregularities or risks [15].

The Fiscal Council's 2019 evaluation raised specific concerns about the lack of transparency regarding fines, penalties, and other compensations, particularly account 245300, which continued to increase. This account was also flagged in the Benford analysis, suggesting alignment between statistical anomaly detection and fiscal oversight concerns. Similar result we found in article by Nikolic at all [17]. The Council also noted that detailed lists of companies receiving budget loans (account 111000) were missing. However, this particular account was not flagged in the Benford analysis, highlighting a limitation in coverage. Additionally, the Council pointed out problems in the categorization of extraordinary non-tax revenues and the lack of detail regarding dividend payers, directly aligning with the anomaly flagged in account 741200 – Dividends in the Benford analysis.

Application of Benford's Law to 2020 Data

The application of Benford's Law to the 2020 financial data revealed certain anomalies, particularly at the detailed account level (fourth-level data). Accounts beginning with the digits "60" were statistically flagged, and these turned out to correspond to specific budget accounts (212100, 541100, 621200, 732100, 921200) that indeed had notable deviations or special circumstances in 2020. When comparing these results with official sources, we found a strong alignment in several cases:

- The flagged donation account (732100) matched the official report of donations coming in below plan.
- The flagged loans account (621200) corresponded to overspending on financial assets (loans to others) above plan.
- The flagged financial asset receipt account (921200) aligned with an extraordinary 700% jump in that category above plan.
- The flagged liability account (212000, under the "60…" pattern) was implicated by the auditors due to mis-recorded transactions involving bond discounts

Application of Benford's Law to 2021 Data

Testing the first-digit distribution of the full dataset at the third level of economic classification revealed no statistically significant anomalies. The data conformed well to Benford's Law. However, a first-two digits test was not conducted for this dataset, as it contained fewer than 300 observations, making the test statistically unreliable.

In contrast, analysis at the fourth level uncovered nonconformities in the first-digit distribution, specifically for the digits 2 and 6, with Z-statistics of 2.3689 and 1.9789, respectively. Since the critical value for significance is 1.96, digit 2 exceeds the threshold and digit 6 is at the margin. This suggests a potential over or underrepresentation of these digits compared to Benford expectations.

Total of 64 accounts were identified where values begin with one of the flagged digits. These accounts range from 015100 (Non-financial assets in preparation) to 922200 (Loan repayments from foreign governments). Additionally, the Chi-square test also confirmed nonconformity of the overall digit distribution at this level.

Further, the first-two digit analysis showed significant deviations for combinations 41, 61, and 82, suggesting that a subset of 21 economic classifications—ranging from 112200 (Loans to foreign governments) to 733100 (Current transfers from other government levels)—may warrant further scrutiny.

The Balance Sheet data was also tested for conformity with Benford's Law. The first-digit Z-test indicated a significant anomaly for digit 4, with a Z-statistic of 2.2512, exceeding the critical threshold. Eighteen accounts were identified as beginning with these anomalous digits, including 021300 (Goods for resale) and 311500 (Sources of cash funds). Again, the first-two digits test was not applied due to the dataset containing fewer than 300 records.

The Income Statement showed a statistically significant deviation for the first digit 8, with a Z-value of 2.1623. This exceeds the threshold and may indicate anomalies in the frequency of values starting with that digit. Fourteen accounts were involved, but like in previous cases, no first-two-digits test was applied due to limited sample size.

The analysis results were compared against the Law on the Final Account of the Budget of the Republic of Serbia for 2021. Several key deviations identified in the Benford analysis align with irregularities or performance gaps highlighted in the official reports: Non-tax revenues (class 74) exceeded planned amounts, which corresponds with anomalies in Benford results for this class; Donations (classes 73 and 74) and other non-tax revenues from indirect beneficiaries (class 78) also exceeded expectations. These were flagged as suspicious in Benford's analysis. Deviations were also observed in the financing account categories, particularly class 91 (foreign borrowing), class 92 (sale of financial assets), and class 61 (domestic borrowing), which correspond to accounts like 922200 (highlighted in the test).

The State Audit Institution (SAI) report for 2021 emphasized several accounting issues: Certain funds were not recorded in the Treasury's General Ledger or not recognized as current-period revenues, especially under economic classification 912 (foreign borrowing receipts); Overstatements in current expenditures and expenses were noted, as well as omissions related to receivables and obligations, such as: Account 122100 (Receivables from unpaid revenues), Account 291300 (Receivables from asset sales), Account 242000 (Subsidy obligations), Account 245000 (Other expenditure obligations), Among these, all but account 245000 were confirmed by Benford analysis as being potentially problematic, strengthening the case for further examination.

The Fiscal Council further supported these concerns in its 2021 commentary: The use of the current budget reserve exceeded what was officially disclosed in legal bulletins. The reserve was used as a flexible mechanism to address pandemic-related emergencies. Benford analysis confirmed significant expenditures through this channel. The lack of transparency in investment attraction subsidies was criticized [18]. Specifically, account 454000, along with 482300 and 212200, lacked detailed justifications. These accounts were also identified in the Benford results as areas of concern.

Application of Benford's Law to 2022 Data

At the third aggregation level of the dataset, the first-digit conformity test did not reveal any significant deviation from Benford's expected distribution, suggesting a general consistency in the numerical structure of the data. Due to the small dataset size (fewer than 300 observations), the first-two-digit test was not applied at this level, in accordance with established methodological thresholds for statistical significance.

In contrast, the first-two-digit test conducted at the fourth data aggregation level revealed significant anomalies for digit combinations 17, 31, 46, 50, and 84. These digit patterns correspond to 32 distinct economic classifications, including accounts ranging from 123200 – Advances, Deposits, and Guarantees Given to 921900 – Proceeds from the Sale of Domestic Shares and Other Equity. These results indicate possible areas of irregularity that merit further scrutiny, particularly where these classifications overlap with fiscal deviations identified in official reporting.

Tests on the Balance Sheet data did not detect any first-digit or first-two-digit anomalies, again due to the small sample size. Similarly, the Profit and Loss Statement (Income Statement) showed no deviations in the digit distribution.

An examination of the Final Budget Account Law of the Republic of Serbia for 2022 reveals that non-tax revenues (class 74) significantly exceeded the planned amounts. Conversely, donations (classes 73 and 74), subsidies (class 45), grants to mandatory social insurance organizations (account 464000), and other current expenditures (classes 43, 48, and 49) fell below budgeted expectations. On the financing side, the report documents that borrowing revenues (class 91) and loan repayments not associated with public policy implementation (class 61) were lower than planned. In contrast, proceeds from domestic financial asset sales (class 92) exceeded expectations, and expenditures for purchasing financial assets unrelated to public policy (class 62) were reported to be nearly three times the planned level.

In this context, the results from Benford's Law analysis reinforce the significance of deviations in classes 74 and 92 - both flagged as notable in the statistical tests and confirmed as budget execution outliers in the official report. These overlaps suggest a meaningful correlation between statistical anomalies and real-world financial irregularities or unexpected outcomes.

The State Audit Institution's Report on the 2022 Final Account highlights specific accounting misclassifications. Notably, it points to a misstatement of short-term securities obligations, which were incorrectly reported under account group 211000 instead of 221000. Additionally, the report identifies an understatement of liabilities as of December 31, 2022, particularly in economic classification class 23, and groups 242, 245, and 25. Among these, class 23 was also identified in the Benford analysis, lending further credibility to the statistical anomaly and supporting the conclusion that this classification may involve reporting or accounting discrepancies.

The Fiscal Council's assessment emphasizes systemic procedural concerns, especially the widespread use of the current budget reserve to finance public policy expenditures (class 62). This practice bypasses formal budgetary approval processes, thus reducing fiscal transparency. However, the Benford analysis did not flag class 62 as anomalous. This discrepancy underscores a known limitation of Benford's Law: while effective at detecting irregularities in the distribution of numerical data, it may not capture procedural or classification-related concerns that do not produce statistically unusual digit patterns.

In summary, the analysis for 2022 demonstrates that the application of Benford's Law can effectively identify areas of potential concern, particularly where numerical irregularities align with known fiscal deviations. The identified classes - particularly 74 and 92 - were both statistically flagged and documented in budget execution reports as significantly deviating from the plan. Class 23, also identified through statistical testing, was the subject of audit criticism regarding reporting accuracy. However, some relevant procedural concerns, such as the misuse of class 62 for public policy spending, were not flagged by the digit-based methodology, highlighting the necessity of combining statistical testing with traditional audit and policy analysis frameworks for a comprehensive assessment.

Subset Largest Growth/Decline Test

This test is especially relevant in public finance, where sudden shifts may indicate accounting anomalies, misclassifications, or policy changes.

As an additional layer of forensic scrutiny, we conducted the Largest Subset Growth Test (LSGT) using economic classification data at the second and third levels for the period from 2019 to 2022. Given concerns regarding the accuracy of inflation statistics reported by the Statistical Office of the Republic of Serbia, we adjusted all data using inflation rates published by the International Monetary Fund (IMF). This step ensures that real (inflation-adjusted) changes are captured more accurately, enhancing the validity of the results. According to IMF data, Serbia experienced the following annual inflation rates: 2018: 2.0%; 2019: 1.8%; 2020: 1.3%; 2021: 7.9%; 2022: 15.1%

All figures were deflated accordingly to identify genuine changes in fiscal flows, rather than nominal distortions caused by inflation.

Key Observations from Second-Level Classification:

The initial results at the second level were complemented by a more granular inspection at the third level, revealing several significant findings:

1. Increase in Non-Financial Assets and Fixed Capital (2020):

   The observed rise corresponds to elevated values in multiple accounts, notably:
   - 011000 (Real estate and equipment)
   - 012000 (Cultivated assets)
   - 014000 (Natural assets)
   - 015000 (Non-financial assets in preparation and advances)
   - 016000 (Intangible assets)
2. Monetary Assets and Short-Term Investments (2021–2022):

   A surge in financial assets is primarily attributed to the sharp rise in account 123000 (Short-term placements).
3. Growth in Long-Term Liabilities (2020–2021): Significant increases in accounts 211000 and 212000 (Domestic and foreign long-term loans) indicate rising debt obligations in these years.
4. Liabilities for Employee-Related Expenditures (2019–2020):

   The growth in account 230000 (Liabilities from employee compensation) points to an expansion in public employment obligations.
5. Expansion in Other Non-Wage Expenditures (2019–2021):

   Several expenditure categories showed sharp increases:
   - 241000: Interest and related costs (from zero in 2020 to over 24 billion in 2021)
   - 242000: Subsidy obligations
   - 243000: Grants, donations, and transfers
   - 244000: Social insurance obligations
   - 245000: Other miscellaneous liabilities

The rapid rise in these categories suggests either policy shifts or extraordinary expenditures, warranting deeper investigation into their composition and justification.

6. Operational Liabilities Spike (2020):

   A substantial increase in account 252000 (Payables to suppliers) and 254000 (Other payables) reflects elevated procurement and contract activity during the pandemic, with a more than twofold increase from 2018 to 2022.
7. Notable Anomalies in Specific Accounts:
   - Account 413000 (In-kind compensation) showed a pronounced spike in 2019.
   - Account 414000 (Employee social benefits) rose sharply in 2022.
   - Account 416000 (Bonuses and special employee expenses) peaked in 2020 and again in 2022.
8. Private Sector Subsidies (2020):

   Account 454000 (Subsidies to private enterprises) registered a notable increase in 2020, consistent with emergency economic interventions during the COVID-19 crisis.
9. Rise in Other Expenditures (Class 48):

   This was driven by:
   - 484000 (Compensation for natural disasters)
   - 485000 (Compensation for damages caused by state authorities)
10. Growth in Intangible Assets (2019–2021):

    The steady increase in account 515000 (Intangible assets) was a significant contributor to the expansion of fixed capital, and its drivers merit special attention.
11. Inventory Growth (2019, 2022):

    A noticeable increase in inventories, particularly in account 521000 (Commodity reserves), aligns with the findings of the Fiscal Council, which emphasized strategic reserve accumulation in 2022.
12. Debt Guarantees (2022):

    Account 613000 (Principal repayment on guarantees) saw a considerable increase. The Fiscal Council has repeatedly flagged such guarantees as high risk, suggesting that many are unlikely to be repaid by the original borrowers.
13. Acquisition of Financial Assets (2019, 2022):

    Substantial growth in accounts 621000 (Domestic financial asset acquisition) and 622000 (Foreign financial asset acquisition) was observed, signaling state intervention in financial markets or asset portfolios.

14. Revenue from Inventory Sales (2019, 2022): Account 821000 (Proceeds from commodity reserve sales) surged, suggesting strategic inventory management or distress sales during fiscal stress.
15. Land Sales Revenue (2020–2021): Account 841000 (Revenue from land sales) demonstrated a significant upward trend, indicating increased privatization or land monetization efforts.

The Largest Subset Growth Test provided clear and systematic evidence of major shifts in Serbia's public finance accounts between 2019 and 2022. Many of these shifts align with known macroeconomic shocks, such as the pandemic, inflationary pressures, and fiscal interventions [5]. However, several categories—including subsidy disbursements, rapid asset accumulation, and liability spikes—warrant further scrutiny to assess fiscal sustainability, transparency, and adherence to policy objectives.

Conclusions

The analyses of the Final Accounts and the reviewed reports of the State Audit Institution and the Fiscal Council reveal many common points. The forensic tests we conducted could serve as a useful supplementary tool and an addition to already established auditing procedures. We believe that the results obtained indicate potential issues that are also evident in the reports of the aforementioned institutions, but they also offer an alternative perspective and reveal other potential weaknesses in record-keeping and the preparation of the Final Account.

Certainly, forensic tests would provide even greater value if applied to gross balance data, where all economic classifications at the sixth level would be available, and if full access to the planning, execution, accounting, and reporting systems of the Republic of Serbia were granted.

The analysis results in this paper confirm what is also suggested in the available literature: forensic tests are a highly useful supplementary tool to the existing set of methods for verifying the accuracy of certain datasets. However, they should not be used in isolation but rather in combination with other methods. By comparing the results from the reports of the State Audit Institution and the Fiscal Council with the findings from our analysis, we can observe a high level of agreement in the "Largest Subset Growth/Decline Test," which is expected, given that both cases involve methods that compare data with previous years.

Therefore, we conclude that Initial High-Profile Screening Tests and Benford's Law can provide valuable insights into positions not previously flagged as questionable - especially if the same positions appear across multiple reporting years. Given this context, we can more confidently conclude that transactions affecting those positions must be further and more thoroughly investigated.

Just as certain positions may go unnoticed by Benford's Law, others may remain undetected by traditional tests and analyses conducted on the Final Accounts of the Republic of Serbia by the mentioned institutions. Hence, their combined use in both internal and external audits is of immense value.

The exercise of applying Benford's Law to the budget data and cross-referencing with actual budget performance and audits illustrates a comprehensive approach to forensic accounting analysis. It shows how quantitative techniques and official oversight can complement each other in identifying and explaining irregularities in financial records.

The test of Subset Largest Growth/Decline serves as a valuable tool in forensic budget analysis, revealing patterns that may not be readily visible through standard accounting reviews.

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