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Detecting Accounting Fraud in Global Corporations: An Audit-Based Analysis Using Benford's Law

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Abstract – This paper focuses on the problem of Benford Law as the effective statistical method which can help to discover the presence of accounting anomalies among large non-banking MNCs. The data used to perform the study are the initial decimal place distributions of six financial variables using 593 financial items with data retrieved through SEC 10-K filings of 20 global companies over five fiscal years (20202024) namely Revenue, Cost of Goods Sold (COGS), Operating Expenses, Total Assets, Net Income, and Accounts Receivable. These findings suggest that there are statistically significant departures of the data in terms of the distribution of Benford, achieving the chi-square value of 23.642 and the Mean Absolute Deviation (MAD) of 0.0195 highly exceed the critical value of 15.507 and 0.015, respectively. COGS and Total Assets have the most significant degrees of deviation, whereas Accounts Receivable has the least number of deviations. Sectoral analysis shows that the firms in the energy sector have the highest structural divergence; this is associated majorly with the volatility of the commodity prices. Moreover, there was also a steady increase in conformity levels in 2021-24, which can be attributed to post-pandemic regulatory changes. The research findings are that Benford Law although it is a good preliminary audit screening can never be utilized alone as evidence of fraud. When used in conjunction with more general forensic accounting methods, its usefulness improves greatly.

Keywords: Benford Law; Detection Accounting Frauds; Forensic Accounting; Chi-square test; Mean Absolute Deviation; Multinationals; Audit analytics; Financial reporting; SEC10-K; digit distribution.

1. INTRODUCTION

One of the most threatening and harmful threats in the capital markets across the world is the financial statement fraud. The high-profile collapse of Enron, WorldCom and Wirecard showed that, it is possible that several years of modified financial statement records can go unnoticed, including via formal audits. The scope of the old conventional sampling-based auditing becomes more evident as multinational corporations are becoming bigger and more complex, thus producing huge volumes of the transaction data in multiple countries. Even the most determining effort by auditors cannot be computerized to go through all the records of hundreds of thousands of records, and therefore, small manipulations which are deeply integrated in large datasets will just pass unnoticed. This poses an actual necessity of complementary, data methods that are capable of sweeping huge amounts of financial information in a very short period of time and identify any suspicious trends to be investigated further. This is what Benford in his Law provides. It is a scientific fact established through mathematics, which explains the distributions of the digits in the first place of numbers extracted out of natural processes. Instead of the even distribution of smaller digits, smaller numbers are found in the front of the numbers much more frequently than it was previously. In particular, the number 1 is the leading one with estimated 30.1 percent of leading cases, and the number 9 only has 4.6 percent of leading cases. The full table on the probability of any one of the first digit's d is as follows:

$$\mathbf{P(d) = \log_{10} (1 + 1/d), \; d \in \{1, 2, 3, \ldots, 9\}}$$

This trend is likely to disintegrate when financial information is produced or distorted in a perverted way. Individuals who coin numbers will introduce more equal distribution of numbers, or dislike certain digits combinations and possess a quantifiable difference between the natural distribution and the records that resulted. This is the gap that is recognized by the Law by Benford. Although the idea of data-driven auditing has become more popular, the research has rarely been piloted on a large and multi-sector sample of the global firms over a period of years. The present research seals the aforementioned gap since it takes the Law of Benford and compares 20 large multinational corporations in eight industries between 2020 and

2024 to assess the reliability of the two statistical measurements.

2. REVIEW OF LITERATURE

2.1 Theoretical Foundations of Benford's Law

There is some theoretical basis behind the Benford law, and this section discusses it. Benford Law was mathematically proved when Hill (1995) demonstrated that in the case when data is sampled by a large and heterogeneous mixture of distributions (financial records are of this nature by nature), the most frequent digits followed a logarithmic distribution. It was not mere curiosity and when the law attained such rigour it allowed its auditors and research workers to depend on it. Hill made the pattern of logarithm tables noted by Newcomb (1881) relevant to the analysis of real-life data.

2.2 Nigrini's Audit Applications

The initial investigator who took Benford Law to the accounting practice was Nigrini (1996, 1999). Using it on data on tax returns, he demonstrated that values which were modified or falsified gave out digit distributions that were measurably different to those in the Benford Law. The two key measures that exist in practice today are formalized in his book of 2012, both the Chi-Square goodness of fit test to have statistical significance, and the Mean Absolute Deviation (MAD) to have a measurement of the size of the deviation. These are still the standard tools in the audit research of Benford. The policy that is extended to digital auditing is 2.3.

2.3 Extending to Digital Auditing

Drake and Nigrini (2000) have proven that Benford Law is particularly effective when used in combinations with the computer-assisted audit tools (CAATs) since computer-based system can use the test on a whole dataset instead of on samples. This introduction was a significant change since before handing out a few hundred entries, the auditors were able to filter hundreds of thousands of records and leave the digit test pointing out which ones to scrutinize further.

2.4 Cautions and Boundaries

Overall, Durtschi, Hillison, and Pacini (2004) have given a very critical counterbalance of the Law on Benford and revealed that the Law is not applicable to all datasets the same way. It works best on quantities that vary across a number of orders of magnitude as well as those that occur naturally like revenues, expenses and assets. It is inefficient with limited or set numbers which are in the case of fixed salaries or controlled prices. Rauch et al. (2011) provided another warning: the fact that it is not distributed in accordance with the expectations does not necessarily indicate that it was done with fraudulent intentions. The legitimate deviation can be due to industry-specific patterns, the size of business and reporting conventions. In this paper, clear consideration has been made of such warnings through the role of analysis of structural drivers and the results of statistics.

2.5 Forensic Accounting Applications

Some of the first forensic evidence to be presented in Carslaw (1988) and Thomas (1989) depicted that the patterns of the digits in the financial statements could provide evidence of earnings manipulation especially the rounding of the figures near the psychological threshold. Beneish (1999) constructed complementary ratio-based devices of identifying earnings manipulation. The combination of the works has been the creation of a tradition of quantitative digit and ratio analysis as a layer of first-pass fraud detection - a tradition that this study embraces and further building on. interpretation of findings.

2.6 Recent Advances in Multi-Metric Testing

Leonov (2022) demonstrated that Benford analysis can be significantly enhanced to the levels of detecting mild manipulation by going beyond the first number and using second numbers, which the former test fails to do. Jianu, Jianu, and Ghiță (2021) affirmed that the distribution deviation, as expected by Benford, is an effective indicator of a reporting error, however, it should be interpreted in context, a result should never be interpreted just as the knowledge of the normalcy of that particular industry and business. These new additions have a direct role in influencing this research in terms of dual-metric approach and its sector-specific. The Future of Benford Analysis 2.7 Machine Learning.

2.7 Machine Learning and the Future of Benford Analysis

The authors of the study by West and Bhattacharya (2016) showed that the performance of Benford Law and machine learning classifiers in detection of fraud is significantly higher than that of any of the methods. Ngai et al. (2011) also demonstrated that the methods of data mining such as clustering and classification, which can be used to supplement digit distribution tests in determining anomalies which would otherwise remain undetected, is effective. This is an indication of a new hybrid way of Benford screening that is used to select applicants that will be subjected to further analysis using algorithms, as opposed to a verdict itself. This research

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provides a basis of empirical studies to such a comprehensive structure.

3. RESEARCH METHODOLOGY

3.1 Data Collection and Sample

The type of research in this study is a secondary-data, quantitative, research design. The sample involved 20 non-banking multinational corporations (30,000 employees, 2020 fiscal years) in eight sectors to obtain financial data that were publicly available annual reports and SEC EDGAR 10-K filings in 2020 to 2024. The companies were selected in relation to global operation size, permanent public listing, and multi annual reporting. Entries that contained a zero or negative value (which could not have a leading value in any meaningful way) were discarded, and 593 useful observations remained. Table 1 summarizes the constitution of the dataset.

Table 1: Dataset Summary

Parameter	Details
Sample Size	20 Non-Banking Global Corporations
Study Period	Financial Years 2020 – 2024
Total Observations	593 data points (zeros and negatives excluded)
Financial Variables	Revenue, COGS, Operating Expenses, Total Assets, Net Income, Accounts Receivable
Sectors Covered	Technology, Energy, Automotive, Healthcare, Consumer Goods, Retail, Telecom, Electronics
Countries	USA, South Korea, Japan, Switzerland, Germany, UK / Netherlands
Data Sources	SEC EDGAR 10-K Filings, Company Investor Relations Portals
Currency	USD (in thousands)
Statistical Tools	Chi-Square (χ^2) Goodness-of-Fit Test; Mean Absolute Deviation (MAD)

Source: SEC EDGAR 10-K filings and Company Investor Relations Portals (2020–2024).

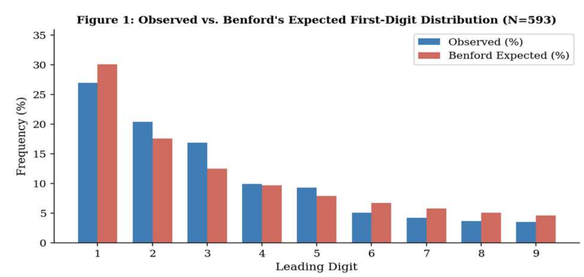
Table 1 illustrates a wide scope of the dataset, nine parameters which determine the scope and content of the study, including six variables of the financial variables based on 20 corporations in 6 countries and across 8 sectors. This is a significant diversity- findings do not apply in one country or industry but reflect trends in a large spectrum of business environments worldwide.

3.2 Statistical Framework

It involved two complementary statistical tests that were applied after gaining first digits of all qualitative financial entries. The Chi-Square goodness-of-fit test (2) is used to compare the difference between the observed and the expected counts of the figures: a value higher than 15.507 (df = 8, 0.05 = 0.05) is a deviation realistically clarified by chance alone. The Mean Absolute Deviation (MAD) is the measure of the mean size of the deviation involving all of the nine digits - the MAD higher than 0.015 signifies non-conformity according to Nigrini (2012). It is necessary to utilize both tests simultaneously: in the case of Amazon, they can pass the χ 2 test (12.82) and fail in MAD (0.064), demonstrating how a single measure may overlook actual anomalies. Analysis was conducted at four levels, aggregate dataset, individual company, financial variable, and year.

4. DATA ANALYSIS AND RESULTS

4.1 Overall First-Digit Distribution



Benford's Expected First-Digit Distribution (N = 593, 2020–2024). Blue bars = actual data; red bars = Benford prediction

Table 2: Observed vs. Expected First-Digit Distribution (N = 593)

Digit	Observed Count	Observed %	Benford's %	Assessment
1	160	26.98%	30.10%	⚠ Minor Deviation
2	121	20.41%	17.61%	⚠ Minor Deviation
3	100	16.86%	12.49%	⚠ Minor Deviation
4	59	9.95%	9.69%	✓ Conforms
5	55	9.28%	7.92%	✓ Conforms
6	30	5.06%	6.70%	✓ Conforms
7	25	4.22%	5.80%	✓ Conforms
8	22	3.71%	5.12%	✓ Conforms
9	21	3.54%	4.58%	✓ Conforms

Source: Computed from annual reports and 10-K filings (2020–2024). Expected values per Newcomb (1881) and Benford (1938).

What Figure 1 and Table 2 indicate: The blue bars symbolize the frequency of each of the leading digits in the financial data

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themselves. The red bars depict the prediction of the law of Benford. At the different points of the bars, there is a deviation. Numbers 1, 2 and 3 demonstrate the most lucid disparity with number 1 being underrepresented whereas numbers 2 and 3 are overrepresented. This does not mean that there is fraud. The major portion of companies in this research state their revenues and assets as USD 200 -399 billion, that is, more numbers are naturally starting with 2 or 3. After digit 4, the bars become close to each other - it is here that the data acts as predicted by the Benford Law. The most important thing to note in Figure 1 is that the entire form of the data conforms to Benford curve to a reasonably good extent, but the deviations at the left-hand side of the scale of numbers are statistically significant and could be investigated more. This is what inspired the further company and industry level analysis below.

4.2 Aggregate Statistical Results

Table 3: Aggregate Chi-Square and MAD Results

Measure	Computed Value	Benchmark / Threshold	Decision
Chi-Square (χ^2) Statistic	23.642	15.507 (df = 8, α = 0.05)	**Reject H_0 — Significant Deviation**
Degrees of Freedom	8	-	-
Mean Absolute Deviation (MAD)	0.0195	> 0.015 = non-conforming	**Non-Conforming**

Note: Both H_{01} and H_{02} rejected at $\alpha = 0.05$.

What Table 3 indicates: There are two numbers that are important here. To begin with, the 23.642 is far beyond the 15.507 mark - this informs us that the difference which we observe in the data is not simply caused by sheer coincidence. It is also statistically real. Second, MAD of 0.0195 is greater than the 0.015 line indicating non-conformity. Combined with the findings of the previous section, these two outcomes prove: the financial data of these 20 companies is not the result of the expectation of Benford as a standard data should be. That is flag worth looking at--not, however, that it is, by itself, fraud. The number 3 is the individual highest contributor of the high 23.642 9.062 represents an individual contribution to the high 3. This is directly connected to the fact that most companies in this sample (specifically in the Energy and Technology sectors) consistently state revenue and asset amounts ranging between USD 300-399 billion making the number 3 much more common than Benford would expect to occur in a dataset with natural range.

4.3 Company-Level Analysis

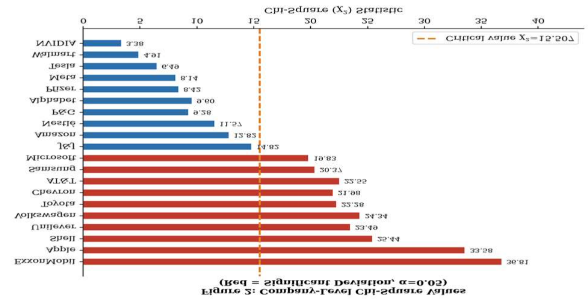

Figure 2: Chi-Square Values by Company. Red bars exceed the critical threshold (χ^2 > 15.507), indicating statistically significant deviation from Benford's Law.

What Figure 2 demonstrates: Fig 2 is split into bars each of which symbolizes one company. The cut-off points χ 2 = 15.507 is indicated by the orange dashed line, and bars to the right of it are statistically significant. Ten out of the 20 companies move past this limit. The biggest deviations are presented by ExxonMobil and Apple, the smallest ones by NVIDIA and Walmart. It does not matter that specifically these companies diverge, but the reasons are as follows: the revenues of ExxonMobil almost increased threefold in 2020 to 2022 because of oil prices skyrocketing, pushing numbers to the scope of 23 numbers. The COGS and asset numbers that are used by Apple are always in large scale and constant, starting with 2. These are structural trends; it is not an indication of manipulation - but should receive greater audit scrutiny.

On the other side of the scale, one can find the most similar results with the Benford Law in NVIDIA (2 = 3.379) and Walmart (2 = 4.906). The revenues of NVIDIA increased significantly between USD 16.7B and USD 130.5B during the research period - such a wide series of results is bound to yield mixed first digits that reflect the forecast of Benford. The millions of varied transactions of Walmart every day, in a wide variety of products, qualities, and prices, produce just the type of naturally distributed digit distribution that can be described by the Benford Law. Both instances affirm that law functions successfully as a conformity metric in instances when business operations are truly diverse and not limited to a finite number.

4.4 Sector-Level Analysis

Table 4: Sector-Level Benford's Law Conformity Analysis

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Sector	n	χ² Statistic	Key Observation
Technology	150	13.52	Borderline — monitor COGS and Total Assets
Retail / E-Commerce	60	8.84	Best conformity — naturally diverse transactions
Automotive	90	20.17	Significant — multi-currency and cost clustering
Energy	86	50.44	Highest deviation — extreme commodity price swings
Healthcare	60	18.23	Significant — rapid pharma revenue swings
Consumer Goods	90	19.81	Significant — CHF/GBP/USD translation effects
Telecommunications	27	22.55	Significant — restructuring and impairment charges
Electronics	30	20.37	Significant — semiconductor revenue cycle effects

Source: Aggregated from company-level data. χ² critical value = 15.507 (df = 8, α = 0.05). Six of eight sectors show significant deviation.

What Table 4 reveals: Red χ 2 values in the third column are above the critical value and result in a follow-up; green values are conformable. Eight out of the 10 sectors are red. Managerial variations theory M E/M behaviors Eare significant with χ 2 = 50.44 - more dramatic than thrice the threshold. This is wanted by drastic fluctuations in the oil prices in the years between 2020 and 2024, that squeezed the revenues of the company in a small range of values beginning with the same numbers. The best result is in Retail and E-Commerce (X 2 = 8.84) since it consists of the millions of small transactions that are diverse and quite spread across, producing immediately a spread of the leading digits.

The position of Technology is in a borderline state (χ 2= 13.52) right below the line. It is a temporary puzzle: The fast revenue growth in the broad spectrum of NVIDIA makes the numbers of the company digit distributions diverse and close to those ones predicted by Benford, whereas the steadily high numbers of Apple and Microsoft in the hundreds-of-billions category push the picture of the industry out of the desired curve. This is a significant methodological fact that the sector-level averages may conceal the company-level variation and this is why both levels of analysis are required.

4.5 Year-Wise Conformity Trend (2020–2024)

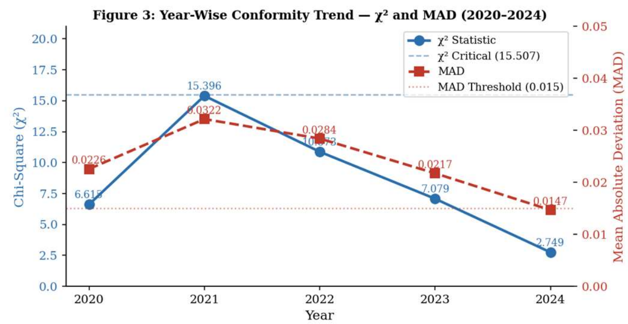

Figure 3: Year-wise Benford's Law Conformity Trend (2020–2024). Blue line (left axis) = Chi-Square values; Red line (right axis) = MAD values. Dashed lines mark thresholds.

What Figure 3 is demonstrating: This chart is tracking how the data was following Benford Law over the years. The lower the values are, the better the conforming. The blue line (χ 2) and the red line (MAD) both indicate a distinct downward trend between 2021 and 2024 -that is, the conformity became increasingly better. The worst is in 2021: this was the year of the international economic recovery, when the revenues bloomed and were concentrated in particular ranges of digits. By 2024, 2 (20) = -2.749 (far less than the critical line) and MAD =0.01468 (the lowest adversary of the research period). This is a positive indication that more post-pandemic regulation is enhancing the naturalness of the financial reporting.

It is interesting especially the 2020 result. The pandemic had a devastating effect on the economy, but the extent of digit performance increased instead of reduced, since pandemic-induced revenue constriction put numbers in a broader range of numbers, resulting in more organic digit diversity. This paradoxical result demonstrates that Benford conformity cannot be merely a moderator of good economic times: it corresponds to the structural diversity of the numbers as such, and can enhance even in the context of the underlying business environment being under pressure.

4.6 Financial Variable Analysis

Table 5: Benford's Law Conformity by Financial Variable

Financial Variable	χ^2 Statistic	MAD	Conformity Status
Revenue	14.951	0.03175	Acceptable
Cost of Goods Sold	28.139	0.04935	⚠ Non-Conforming — Highest Risk
Operating Expenses	12.892	0.03175	Acceptable
Total Assets	23.475	0.04422	⚠ Non-conforming
Net Income	11.081	0.02230	Acceptable
Accounts Receivable	4.549	0.01735	✓ Closest to Benford Baseline

Source: Computed from 20-company dataset. χ^2 critical value = 15.507 (df = 8, α = 0.05). MAD threshold > 0.015 = non-conforming per Nigrini (2012).

Table 5 reveals that there is a different financial variable in each row. The values of red are above the value it should be and those of green are in the range. COGS is the most dangerous variable with 28.139 2 -tests, and this is almost twice the significant level. This is important since the COGS gives the most direct impact of the inventory accounting decisions (FIFO and LIFO) and timing decisions, which are often implemented in income management. The second measure that is most deviant is Total Assets. The Accounts Receivable fits the best on the other end- it includes huge volumes of invoices with many different customers with many different balances with them, which organically generate the number variety which Benford Law characterizes. Although the Net Income is closely linked with earnings management in the scholarly research, the variation is moderate in this case. This is probably due to the fact that values of net income differ drastically between companies and years net income is close to zero in crisis years and high amounts in non-crisis years which naturally spread out the top digits. The values of Revenue and Operating Expenses are also not overly large, indicating that these items in the line are less likely to be affected by structural digit clustering of the scale of this sample.

5. HYPOTHESIS TESTING Table 6: Hypothesis Testing Summary

Hypothesis	Statement	Test Result	Conclusion
H_1	Benford's Law detects accounting anomalies in global corporations	$\chi^2 = 23.642 > 15.507$ → Reject H_{01}	Supported ✓
H_2	Deviations from Benford's Law are associated with financial data anomalies	MAD = 0.0195 > 0.015 → Reject H_{02}	Supported ✓

Source: Statistical analysis of 593 observations, 20 corporations (2020–2024). Both null hypotheses rejected at α = 0.05.

What table 6 demonstrates: Both the hypotheses are accepted. The fact that the total 0 2 of the result is more than the critical value supports H 0 because this value indicates that statistically significant deviation was observed in this dataset by the Benford Law. The H 2 is validated by the fact that the MAD value is over 0.015 implying that the magnitude of such deviation is significant to be associated with the possibility of data anomalies. Most importantly this does not point out to fraud. It implies that the data assumes patterns that are not representative of what normally occurring financial figures are supposed to appear like and the abnormalities are clustering in the variables (COGS, Total Assets) and industries (Energy, Automotive) in which the manipulation risk has been identified to be acute. It should be noticed that structural explanations of the firm size, commodity prices, multi-currency impacts, account a substantial percentage of the deviation. The null hypothesis in both cases being rejected should be taken as an indication that: Benford Law was able to find patterns that are not in line with natural baseline and the patterns are concentrated in high risks that needs further scrutiny at the audit level. This is precisely the purpose that the tool is meant to take.

6. DISCUSSION

6.1 What the Deviations Actually Tell Us

The most interesting interpretation made in this research article is that lack of conformity to Benford of Law is not synonymous with fraud. This difference is of the first import in itself. Most of the non-conformity in this sample directly follows to observable structural factors: Those companies with reported revenues and assets that fall within USD 200-399 billion size bracket, shocking commodity prices that force natural revenues in the Energy sector into specific digit bands, multi-currency translation resulting in systematic dropping or adding a digit changes and events of rapid growth/contraction that require a period of time to smooth out the natural spread This is most visible in the case of ExxonMobil whose revenue has almost tripled in two years, which is economically dramatic but whose result can be explained with the clear perspective of the oil prices. Their deviation is factual, their reason is structural. Nonetheless, it is a noteworthy overlap that, the COGS and Total Assets of the highest manipulated risk of the two items of the forensic accounting literature also represent the highest Benford deviation in this study. These did not occur by accidents. Even in the presence of structural explanation, auditors and regulators are advised to take the high value of χ 2 and MAD in COGS and Total Assets as a real indicator to be researched. The rising trend of 2021-24 is also indicative of a stricter post-pandemic regulation being generated to generate tangible gains in the naturalness of reported figures demonstrates that a policy result could be identified useful to regulatory bodies. .

6.2 Practical Implications for Auditors and Regulators

The practical implication of this research on audit professionals would be that Benford Law would make a better first line screen instead of a definitive decision. It is quick, cheap and scalable- it has the capability of scanning complete financial records as opposed to samples and it enables the little audit time to be concentrated in the records most likely to have irregularities. However, it is necessary to accompany it with more research. The 2-fold 2 -and-MAD method cannot be neglected: as has been seen in the case of Amazon, each and every statistic might overlook the indicators of the other. Industry-specific benchmarks are also not a negligible issue, the level with which one can name a significant anomaly in Retail should not be that, one may employ in Energy. The year-by-year conformity trend is also a tool that regulators could use as the indicator: when the Benford conformity gets worse during a certain year, it is an indicator that financial reporting quality might be decreasing in that time: therefore, regulators can do it earlier.

7. Conclusion

This research entails solid empirical support arguing that Benford Law performs effective audit signal value in case it is used systematically on big multinational corporate financial data sets. In 593 observations of 20 international firms, 5 fiscal years all over, both, xtau 2- and MAD-tests exceeded the conformity levels. COGS and Total assets became the most significant aspects that should be reviewed by the forensics. The largest deviation was in the Energy industry that was mainly caused by the dynamics of commodity prices. The increasing conformity between 2021 and 2024 indicates the desirable impact of the presence of post-pandemic oversight on regulatory matters regarding integrity of reporting. Simultaneously, this article supports one important warning, which is that statistical nonconformity to Benford Law is not a conclusion but an indicator. It is a guide to the auditors on where to search as opposed to what they find once there. The practical use of the law is the most efficient screening of massive financial data and exposing anomalies that would scarcely be revealed through the traditional sampling techniques. Taken together with internal control testing, financial ratio testing and forensic investigation processes, financial ratio analysis of Benford-based screening will affordably enhance the quality of audit in the era of more difficult, high volume corporate reporting. Future studies can go beyond the banking and insurance industry as presented in this framework and incorporate machine learning classifiers to provide predictive scores of fraud-related risks, analyze the moderating role of corporate governance quality on Benford conformity, and come up with the second-digit extensions that can identify banking and insurance manipulations that cannot be identified by first-digit tests. This defense will always come in handy as data intensive screening systems such as the Law by Benford as volumes of financial full disclosure reports continue to rise steadily.

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