

The Role of the Statutory Auditor in Assessing Fraud Risk in the Revenue Cycle and Methods for its Detection

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Abstract of the master's thesis awarded first place and the Dr Zdzisław Fedak Award in the PANA Competition for the best master's thesis in the field of audit. The thesis, entitled "The Statutory Auditor in the Financial Statement Audit Process, with Particular Emphasis on Fraud and Fraud Detection Methods", was written under the supervision of Agnieszka Mazurek-Czarnecka PhD and defended at the Krakow University of Economics.

Introduction

The financial statements of an enterprise constitute a fundamental source of information for investors. Their content is paramount, serving as the basis for stakeholder inference. Research findings confirm that financial results reported by companies significantly influence their share prices (Balina, Juszczak, 2017, p. 12). Consequently, there exists a temptation to present financial data in a more favourable light than reality dictates, particularly when pecuniary benefits are at stake. Dynamic economic shifts, artificial intelligence, and events classified as "black swans" render the mitigation of this phenomenon increasingly complex, thereby exacerbating the probability of fraud occurrence.

Contemporary fraud detection relies not merely on auditor intuition but on the deliberate application of data analytics and analytical procedures designed to support fraud detection within the revenue cycle. These encompass both conventional techniques, such as trend analysis and regression, and more advanced tools, including Benford's Law and the Beneish M-score model.

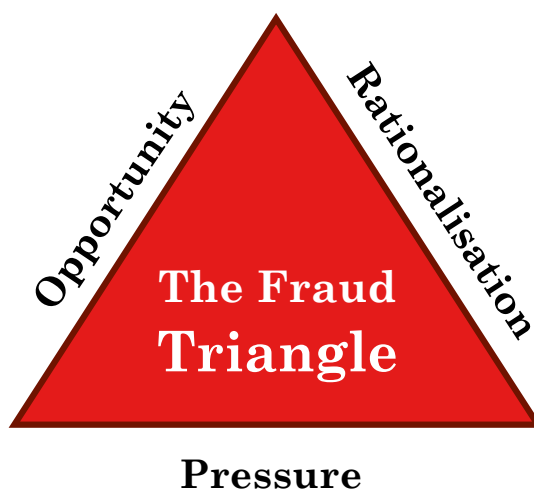
The financial information contained in this paper is not subject to trade secrecy. Certain data and case details have been intentionally modified to better exemplify the specific context of the case. This paper describes only fragments of the financial statement audit; all other procedures were performed in accordance with applicable requirements.



1. Revenue under Scrutiny – The Genesis of Fraud Risk

The revenue cycle has long been recognised as one of the areas most susceptible to fraud risk in financial statement audits. National Auditing Standards unequivocally indicate its critical nature. The significance of this area is further emphasised at both the national and European levels (PANA, 2023). Empirical research corroborates the validity of this approach. According to the Occupational Fraud 2024 report published by the ACFE, the sales function constitutes one of the primary sources of occupational fraud, with 12 per cent of analysed cases originating within sales departments (ACFE, 2024, p. 5).

A valuable instrument for analysing the genesis of fraud within the revenue cycle is Cressey's Fraud Triangle, which delineates three co-occurring factors conducive to fraud: pressure, opportunity, and rationalisation. Originating from research into organised crime, this concept remains one of the cornerstones of fraud risk analysis in accounting and auditing. The fraud triangle is presented in the figure below.



The Fraud Triangle

Source: Author's own elaboration based on Korupcja w Polsce [Corruption in Poland], retrieved from: <https://maciejwnuk.pl/korupcja-w-polsce-12-pandemicznych-impulsow/> (accessed 03.01.2025).

Pressure constitutes one of the fundamental factors conducive to fraud within the revenue cycle.

Deteriorating financial standing, capital market expectations, bonus schemes, and the necessity to comply with debt covenants cause management to experience a strong motivation to intervene in reported sales levels. As a pivotal component of the financial result, revenue becomes a natural locus for potential manipulation under such conditions.

In practice, numerous key financial and non-financial indicators are directly contingent upon sales levels. This pertains to revenue growth dynamics, profitability ratios, Debt-to-EBITDA ratios, and credit covenants. Consequently, the overstatement or accelerated recognition of revenue may lead to the simultaneous improvement of several parameters assessing the entity's condition. Pressure may manifest in highly specific forms: a sales director whose bonus depends on meeting targets may exert pressure to accelerate invoicing at the end of the reporting period, while the management board of a listed company may strive to "meet" forecasts to avert a sharp market reaction. Furthermore, this factor is particularly pronounced in indebted entities, where management faces intense pressure to comply with credit covenants.

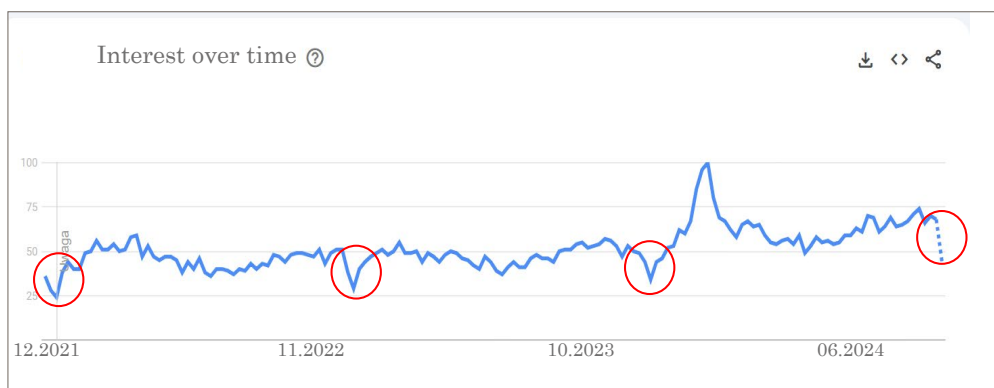
The second important element of the fraud mechanism is opportunity, which frequently stems from the complexity of revenue recognition rules. In practice, this is facilitated by factors such as long-term transactions, related party transactions, and transactions executed around the reporting period cut-off. The fraud itself may result from uncomplicated actions, such as issuing an invoice without actual delivery, recognising revenue prior to the transfer of control over goods, or fabricating warehouse documentation on the final day of the financial year. The simplicity of these activities renders the opportunity literally within reach. A distinct opportunity arises in organisations with undeveloped internal control systems; as research indicates, the internal control system and staff competence significantly influence the risk of fraud (IJEEM, Saputra, Suartana, 2025).

The final component of Cressey's Fraud Triangle is rationalisation, defined as the internal justification for unethical conduct. Cressey observed that perpetrators rarely perceive themselves as criminals, but rather as individuals temporarily borrowing funds or acting in the company's best interest. Within the revenue cycle, rationalisation may manifest as the conviction that the act is merely a timing difference and that sales will materialise in the subsequent period. Another line of reasoning involves acting on the belief that since "everyone does it", then "so can we".

Despite the passage of time, this theory remains relevant, and the revenue cycle exemplifies the premises of Cressey's triangle, combining pressure for results with the potential for manipulation. Analysing the revenue cycle through the prism of

pressure, opportunity, and rationalisation facilitates a deeper understanding of the motives and mechanisms leading to financial statement misstatements.

However, fraud risk is not uniformly distributed throughout the year. Although an analysis of search queries for the phrase “financial fraud” might suggest lower interest in this issue towards the year-end, the professional judgment and experience of the statutory auditor indicate a need for heightened vigilance precisely during this period. The figure below presents data regarding the search popularity of this phrase.



Search popularity of the query “financial fraud” on Google

Source: Author's own elaboration based on Google Trends, retrieved from: <https://trends.google.com/trends/explore?-date=2021-12-15%202024-12-15&q=Financial%20Fraud&hl=pl>, (accessed: 11.11.2024).

Perpetrators of fraud typically do not analyse fraud mechanisms nor seek information regarding them; they simply commit the acts, which explains this inverse correlation.

2. From Figures to Insights – Trend Analysis and Data Dependencies Using Artificial Intelligence

2.1 Fundamentals of Trend Analysis and Regression Methods

Analytical procedures involve, inter alia, comparing actual data with expected values to identify unusual deviations that may indicate irregularities. The process of developing expectations itself can be time-consuming. In this regard, AI-driven tools assist the statutory auditor, and the combination of professional experience and the capabilities of these tools becomes paramount. Their application enhances operational efficiency by enabling the analysis of voluminous industry reports and the synthesis of key conclusions. The utilisation of artificial intelligence tools allows for the completion of 12 per cent more tasks, performed 25 per cent faster (Mollick, Rajendran, 2023, p. 4).

The basis for achieving good results when employing AI-based tools is precise communication with the system. Each query must encompass the context, the problem statement, the AI's persona, the user's position, and the desired output format (Rejzerewicz, 2025).

In the context of this article, the selection of analytical techniques is critical – within the revenue cycle, trend analysis and regression analysis are of primary importance. The former involves comparing financial data and expectations across multiple reporting periods to identify unjustified variations in revenue levels. Graphical representation constitutes the most transparent form of this analysis.

Regression analysis leverages the relationship between data, providing a higher level of analytical assurance. Its essence lies in constructing a model to estimate the expected level of revenue, followed by a comparison with actual data.

Significantly, the application of regression analysis does not require the statutory auditor to possess advanced knowledge of statistical formulae. The model may be constructed using an Excel spreadsheet, with the auditor's key task remaining the correct identification of variables strongly correlated with revenue.

The assessment of the regression model's quality in this tool is based on three metrics:

- R-squared – model goodness-of-fit. Values range from [0,1]; satisfactory measures are: 0.8–0.9 (good fit), 0.9–1.0 (very good fit);
- Standard Error – indicates the precision of the forecast; the lower the value, the more accurate the estimate. It is crucial that this measure remains below 10 per cent of the mean value of the dependent variable or 75 per cent of materiality (AICPA Audit Guide, 2017);

- t-statistic – allows for the assessment of variable significance; typically, the t-statistic should exceed 1.3 (Lachowski, 2019).

Constructing a model that ensures high levels for the three aforementioned metrics allows for high reliability of forecasted sales revenue. The subsequent step involves comparing this forecast with actual revenue and investigating material discrepancies.

2.2. Financial Data Revealing Irregularities – A Case Study of Company X

Entity X is a limited liability company operating in the industry of corrugated paper and paperboard packaging production (PKD code 17.21.Z). Revenue from the sale of finished goods constitutes approximately 96 per cent of the entity's total revenue. Financial reporting is conducted in accordance with Polish accounting regulations, and the entity is not subject to specific sector regulations. The financial statements for the years 2022 and 2023 were subject to a mandatory audit in accordance with the Accounting Act. The audit opinion for 2022 was unmodified.

At the audit planning stage for 2023, the Key Audit Partner (hereinafter "KAP") analysed expected trends and industry demand. Sector reports and expert analyses in PDF format were utilised for this analysis, alongside – to enhance audit efficiency – artificial intelligence (the paid version of ChatGPT). The utilisation of AI is presented in the table below.

Dialogue and Conclusions Derived from AI Utilisation

Prompt Submitted	ChatGPT Response – Report Synthesis
I am conducting an audit of the financial statements for the year 2023 for an entity manufacturing paper, paperboard, and packaging in Poland. What industry demand and sales revenue values should be anticipated for 2023? Utilise industry reports and analyses. Draw conclusions in a few sentences.	According to the CEPI report, in 2023 the paper and cardboard sector in Europe faced limited demand, production downtime, and high manufacturing costs, which translated into a significant decrease in the production and consumption of paper and cardboard. Decline in production and consumption - In 2023, paper and cardboard production in Europe decreased by 12.8% to around 74.3 million tons. - This decline affected all major market segments, including graphic paper (down 27.5%) and packaging paper and cardboard (down 12.2%).
Conclusion	
The Key Audit Partner (KAP) employed AI tools to analyse numerous industry reports to gain a deeper understanding of current market trends. The findings obtained were subsequently cross-referenced with the KAP's professional knowledge and experience. Ultimately, it was assumed that a decline in sales revenue should be expected in 2023, resulting from lower demand and curtailed production within the industry.	

Source: Author's own elaboration based on the paid version of ChatGPT.

The conclusions derived, supported by the KAP's professional experience, pointed to an anticipated decline in demand and a reduction in revenue for 2023. However, the analysis of the financial statements under audit revealed a divergent trend, specifically a revenue increase of approximately 10 per cent. This necessitated a modification of the audit plan and the application of additional analytical procedures, in accordance with KSB 240. The table below presents an excerpt from the audit plan for Entity X.

Excerpt from the Audit Plan for Entity X for 2023

Significant Risk Area	Risk Level (L/M/H)	Identified Risk	Fragment of the Audited Entity's Accounting Policy – Revenue Recognition	Materiality	Planned Analytical Procedures as a Response to Risk
Revenue from sales of finished goods	H – High	Risk associated with the manipulation of revenue from sales of finished goods due to fraud or error.	<i>Revenue from sales of finished goods is recognised in accordance with the Accounting Act, adhering to overriding accounting principles, including the matching principle and the accrual basis.</i>	Overall Materiality: PLN 1,400,000 Performance Materiality: PLN 910,000	Trend analysis/regression analysis utilising ChatGPT

Source: Author's own elaboration.

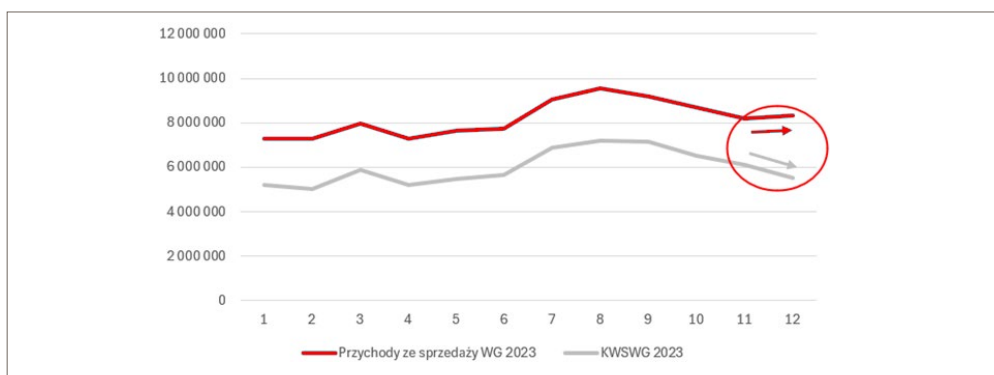
Subsequent procedures involved the analysis of the detailed ledger records for 2023 regarding revenue and cost accounts. The data were reconciled with the trial balance. The dataset was deemed complete and suitable for further analysis. In the next step, a monthly data summary was prepared to facilitate trend analysis and the construction of a regression model. Table 3 presents the aggregated monthly data for Entity X.

Monthly Values of Accounts 700 and 711 of Entity X

Specification	Value in PLN	
Month (2023)	700 – Revenue from sales of finished goods	711 – Cost of manufactured goods sold
January	7,281,186	5,215,252
February	7,275,579	5,037,214
March	7,965,662	5,897,288
April	7,276,248	5,208,529
May	7,655,277	5,469,701
June	7,756,941	5,639,095
July	9,041,581	6,859,324
August	9,553,316	7,207,734
September	9,168,824	7,137,841
October	8,699,700	6,497,758
November	8,193,872	6,105,272
December	8,317,402	5,515,708
Total	98,185,588	71,790,716

Source: Author's own elaboration.

The graphical trend analysis revealed an anomalous divergence in December 2023, characterised by a simultaneous increase in revenue and a decrease in the cost of manufactured goods sold. The figure below illustrates the graphical trend analysis.



Trend Analysis: Revenue from Sales of Finished Goods versus Cost of Manufactured Goods Sold

Source: Author's own elaboration.

Subsequently, a regression analysis was conducted using an Excel spreadsheet, designating revenue from sales of finished goods as the variable Y and the cost of manufactured goods sold as variable X. The model yielded a high R-squared coefficient (approximately 0.93), a low standard error of PLN 219,000, and a statistically significant t-statistic of 4.45, thereby validating it as a highly reliable analytical tool. Next, the predicted values generated by the model were compared with actual revenue figures, enabling the identification of deviations exceeding the standard error threshold. The table below presents this analysis.

Comparison of Predicted Revenue Values with Actual Data and Identification of Deviations

Observation (Month)	Predicted Revenue from Sales of Finished Goods 2023 (Model)	Actual Revenue from Sales of Finished Goods 2023	Residuals (Deviation)	Is the Absolute Value of the Deviation Greater than the Standard Error?
1	7,427,689	7,281,186	-146,503	NO
2	7,252,637	7,275,579	22,942	NO
3	8,098,290	7,965,662	-132,628	NO
4	7,421,079	7,276,248	-144,831	NO
5	7,677,872	7,655,277	-22,595	NO
6	7,844,426	7,756,941	-87,485	NO
7	9,044,197	9,041,581	-2,616	NO
8	9,386,766	9,553,316	166,550	NO
9	9,318,045	9,168,824	-149,221	NO
10	8,688,693	8,699,700	11,007	NO
11	8,302,787	8,193,872	-108,915	NO
12	7,723,108	8,317,402	594,294	YES

Source: Author's own elaboration.

The analysis revealed that December 2023 constituted the sole outlier observation, wherein the deviation between the predicted and actual values significantly exceeded the standard error.

The results of the analytical procedures performed served as the basis for the Key Audit Partner to extend the scope of the audit to include detailed substantive testing focused on the year-end. These procedures confirmed the occurrence of fraud involving revenue overstatement through the incorrect allocation of sales to the reporting period. The total value of the fraudulent misstatement amounted to over PLN 900,000. The statutory auditor issued an appropriate opinion in this regard.

3. Statistics Uncover Irregularities

3.1 Benford's Law as a Fraud Detection Tool

In the literature concerning financial fraud detection, particular emphasis is placed on statistical methods based on Benford's Law (Baryła, 2021, p. 8). Contrary to the intuitive assumption that every digit has an equal probability of occurring in the first position, this law indicates that lower digits appear significantly more frequently than higher ones (Czaja, 2024). The table below presents a comparison of the Benford distribution with the intuitive distribution. For instance, the digit '1' appears as the leading digit in approximately 30 per cent of observations, whereas '9' appears in less than 5 per cent. This empirical regularity constitutes the basis for identifying potential irregularities in large financial datasets.

Benford Distribution versus Intuitive Distribution

Leading Digit	Benford Distribution (%)	Intuitive Distribution
1	30.1	Probability equal for each digit – 11.1 per cent
2	17.6	
3	12.5	
4	9.7	
5	7.9	
6	6.7	
7	5.8	
8	5.1	
9	4.6	

Source: Source: Author's own elaboration based on materials from the Polish Chamber of Statutory Auditors.

Benford's Law does not allow for the identification of specific fraudulent transactions but enables the selection of groups of records that deviate significantly from the theoretical distribution. Such an approach enhances audit efficiency, as it allows for narrowing further procedures to the most suspicious data while simultaneously analysing the entire dataset without the necessity of sampling. The effectiveness of the analysis depends on several key issues. To utilise Benford's Law, it is necessary to first verify the characteristics of the dataset. The table below presents an example test for verifying the input dataset. The more characteristics a given set meets, the closer it approximates the Benford distribution, with the ideal state being the fulfilment of all criteria.

Example Test for Verifying the Dataset in the Context of Benford's Law

Conditions to be Met (Dataset Characteristics)	Met (Yes/No)
All data expressed in the same unit	
Absence of limits in the form of maximum/minimum thresholds (the exception is "zero" in the case of positive number sets)	
Numbers in the set do not represent identifiers (e.g., account numbers, invoice numbers)	
The dataset contains more smaller numbers than larger ones (e.g., the median value is no greater than half of the mean value)	
The dataset consists of multi-digit numbers	
The dataset is extensive (minimum number of observations is 100 – the more, the better)	

Source: Author's own elaboration based on M. Baryła, *Metody wykrywania oszustw finansowych na prawie Benforda* [Methods of Financial Fraud Detection Based on Benford's Law], Cracow University of Economics, 2021.

Following positive verification, the subsequent step involves selecting the type of Benford test. The most frequently employed include the first-digit test, the second-digit test, and the first-two-digits test (Baryła, 2021). In audit practice, the first-digit test typically constitutes the starting point. Its objective is to verify the hypothesis of whether the distribution of the first non-zero digit in the examined dataset corresponds to the Benford distribution.

The procedural steps for the first-digit test (in the case of sales revenue) comprise:

1. Extract records from the accounting ledger into an Excel spreadsheet.
2. Reconcile ledger records to the financial statements.
3. Execute the dataset characteristics test.
4. Select records (e.g., division into two sets: negative and positive).
5. Perform the Benford test (verification of the Benford distribution hypothesis).
6. Compare the analysed database with the hypothetical distribution.
7. Identify records beginning with a digit that does not comply with the Benford distribution.
8. Conduct a detailed analysis of records failing to meet the hypothesis.
9. Draw conclusions.
10. Perform further audit procedures.

The execution of the Benford test itself (step 5) is not a complex process. The simplest method for performing this test is using a spreadsheet (Excel). The table below presents a tabular variant comparing the hypothetical Benford distribution with the actual database.

Summary of Benford Test Calculations

Frequency distribution of the leading digit for the analysed database										Sum
Digit	1	2	3	4	5	6	7	8	9	
A. Frequency										
%										
Hypothetical frequency distribution according to Benford's Law										
Digit	1	2	3	4	5	6	7	8	9	
B. Frequency										
%										
Difference (A-B)										
Difference %										

Source: Author's own elaboration.

In the 'frequency' row, the software counts how many records begin with specific digits (from 1 to 9), while the '%' row calculates the percentage share of these records within the entire analysed population. Subsequently, the obtained results are compared with the theoretical Benford distribution. The accuracy and completeness of calculations are verified by comparing the total number of analysed records with the actual number of items in the dataset (post-adjustments). The table below presents the analysis completeness test. Table cells are automatically populated using Excel spreadsheet functions. Any differences that may arise result from records beginning with the digit '0'. Such items are excluded from the analysis.

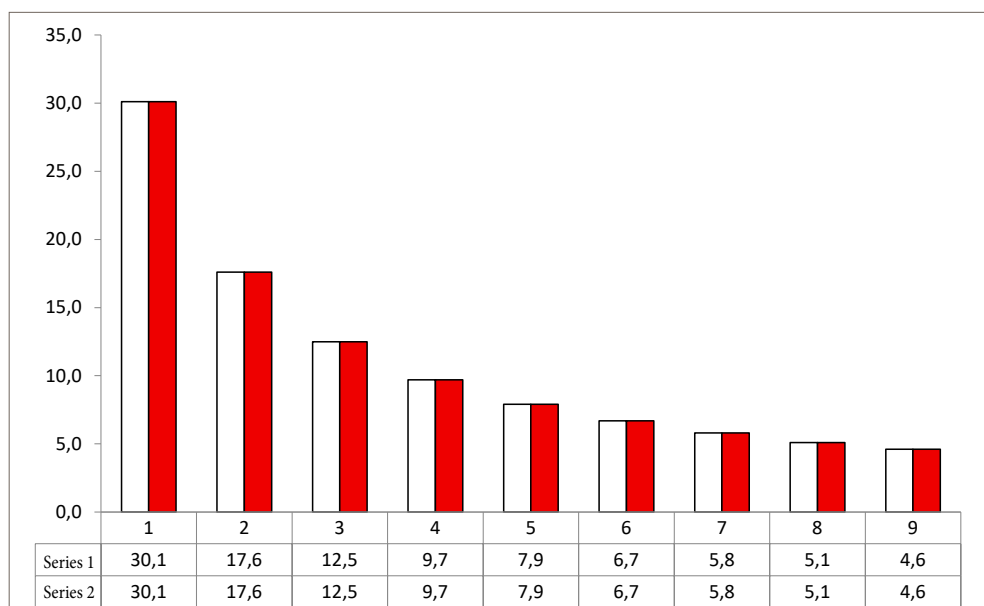
Verification of Benford Analysis Completeness

Actual number of records in the input file	Number of analysed records	Difference

Source: Author's own elaboration.

The final stage of the analysis involves the graphical presentation of the Benford test results, enabling a rapid and intuitive assessment of potential deviations. The figure below presents a comparison of the Benford distribution with the distribution of the analysed database.

Graphical comparison of the Benford distribution (white) with the actual database distribution (red)



Source: Author's own elaboration.

Literature emphasises that there are no rigid thresholds for deviations from the Benford distribution; therefore, the assessment of detected anomalies always depends on professional judgment. In practice, this involves isolating suspicious records and conducting further procedures.

3.2 Digits Speak – Application of Benford's Law in Company Y

Entity Y is a limited partnership operating in the construction aggregates production industry (PKD code 08.11.Z). Revenue from sales of finished goods constitutes almost the entirety of total revenue. Financial reporting is conducted in accordance with Polish regulations, and the entity is not subject to specific sector regulations. During the audit for the previous year, no irregularities were identified. Entity Y held shares in another entity classified as a related party, and there were no changes in accounting policy.

In the audit plan, the Key Audit Partner (KAP) assessed the risk of material misstatement due to fraud in the revenue area as high. Overall materiality was established at PLN 900,000, while performance materiality was set at PLN 585,000 (65 per cent). The KAP obtained the general ledger entries for account 701 – revenue from sales of finished goods in an Excel spreadsheet. The data were reconciled with the trial balance. The statutory auditor confirmed the completeness of the input dataset. The table below presents the format of the received database.

Format of the Database Received for Benford Analysis

A	B	C	D	E	F	G	H	
No.	Account	Date	Document Number	Item	Counterparty	Debit Value	Credit Value	
1	701	03.01.2023	XYZ	XYZ	XYZ	-	4,053	
2	701	03.01.2023	XYZ	XYZ	XYZ	-	8,967	
3	701	03.01.2023	XYZ	XYZ	XYZ	-	2,029	
[...]	[...]	[...]	[...]	[...]	[...]	[...]	[...]	
8817	701	31.12.2023	XYZ	XYZ	XYZ	-	50,211	
TOTAL								62,472,913

Source: Author's own elaboration.

Column A represents the number of records in 2023, corresponding to the number of sales invoices, while their value is recorded in Column H. The table below presents the suitability test performed. It confirmed the validity of applying Benford analysis to the received revenue database (all criteria were met). 47 negative records (adjustments) were identified, eliminated from the database, and designated for separate analysis. No further adjustments were required. The final database comprises 8,770 records.

Database Suitability Test for Benford Analysis

Conditions to be Met (Dataset Characteristics)	Met (Yes/No)
All data expressed in the same unit	YES – Uniform currency unit (PLN).
Absence of limits in the form of maximum/minimum thresholds (the exception is “zero” in the case of positive number sets)	YES – The sole limitation is zero for positive numbers (following elimination).
Numbers in the set do not represent identifiers (e.g., account numbers, invoice numbers)	YES – The figures represent sales revenue values.

Conditions to be Met (Dataset Characteristics)	Met (Yes/No)
The dataset contains more smaller numbers than larger ones (e.g., the median value is no greater than half of the mean value)	YES – The median of the dataset is 1,652.78, while half of the mean value is 3,560.53.
The dataset consists of multi-digit numbers	YES – The database range encompasses sales revenue records from 0.10 to approximately 600,000.
The dataset is extensive (minimum number of observations is 1000 – the more, the better)	YES – The dataset contains 8,817 elements (records) prior to adjustments.

Source: Author's own elaboration.

The Key Audit Partner (KAP) performed the first-digit test in accordance with Benford's Law, utilising Column H of Table 11 (sales value). The results of the analysis are presented in the table below. Out of 8,759 records, 2,965 commence with the digit '1', constituting 33.9 per cent of the database, whereas the Benford distribution posits 30.1 per cent.

Benford Test Results for the Analysed Database of Entity Y

Frequency distribution of the leading digit for the analysed database										Sum
Digit	1	2	3	4	5	6	7	8	9	
A. Frequency	2965	1380	955	760	607	473	397	510	712	8759
%	33.9%	15.8%	10.9%	8.7%	6.9%	5.4%	4.5%	5.8%	8.1%	100
Hypothetical frequency distribution according to Benford's Law										
Digit	1	2	3	4	5	6	7	8	9	
B. Frequency	2636	1542	1094	849	694	586	508	448	402	8759
%	30.1%	17.6%	12.5%	9.7%	7.9%	6.7%	5.8%	5.1%	4.6%	100
Difference (A-B)	329	-162	-139	-89	-87	-113	-111	62	310	
Difference (%)	3.8	-1.9	-1.6	-1.0	-1.0	-1.3	-1.3	0.7	3.6	

Source: Author's own elaboration.

Subsequently, the Key Audit Partner verified the completeness of the test by comparing the number of analysed records with the input database. The results are presented in the table below.

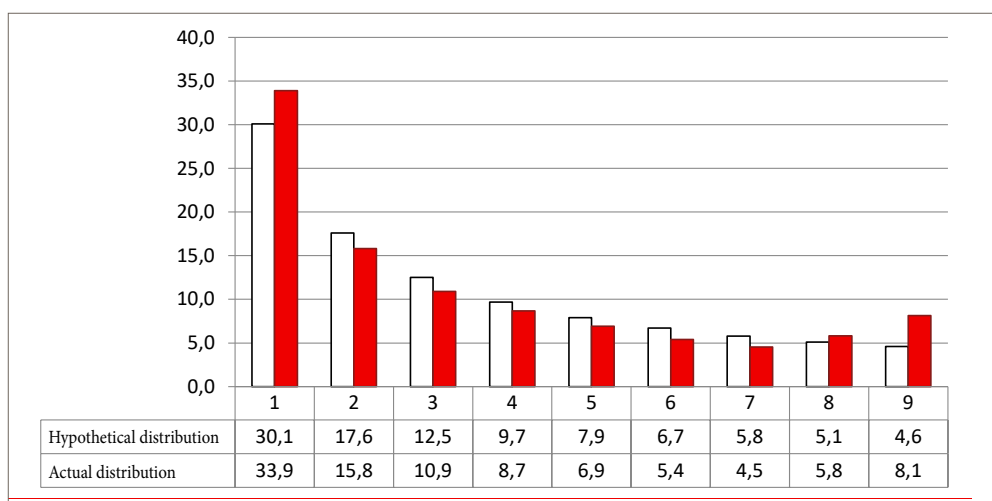
Verification of Benford Analysis Completeness for Entity Y

Actual number of records in the input file	Number of analysed records	Difference
8770	8759	11

Source: Author's own elaboration.

The difference of 11 items results from the occurrence of values beginning with the digit '0', which, according to the theory, are not subject to analysis. The Key Audit Partner confirmed the completeness of the procedure. The results are presented graphically in the figure below.

Graphical Results of the Benford Test for Entity Y



Source: Author's own elaboration.

Based on professional judgment, the KAP determined that deviations exceeding 2 per cent required further analysis. Records beginning with the digits '1' and '9' were selected for detailed inspection, while the remainder were deemed not to carry significant risk. These records were filtered based on Column H, i.e., sales value.

The analysis of items commencing with the digit '9' revealed no irregularities and was justified by the specific nature of the entity's operations (recurring sales of full truckloads of aggregate). The KAP verified the auditee's price list and multiplied the rates by quantity. In the case of records beginning with the digit '1', the majority of transactions also raised no objections; however, recurring sales amounts involving a related party were identified, which raised the KAP's concerns. Examples of questionable transactions are presented in the table below.

Example of Questionable Records Identified Using Conditional Formatting in an Excel Spreadsheet

A	B	C	D	E	F	G	H
No.	Account	Date	Document Number	Item	Counterparty	Debit Value	Credit Value
51	701	05.01.2023	XYZ	XYZ	XYZ – related party	-	11,321
54	701	05.01.2023	XYZ	XYZ	XYZ – related party	-	1,880
188	701	13.01.2023	XYZ	XYZ	XYZ – related party	-	11,321
189	701	13.01.2023	XYZ	XYZ	XYZ – related party	-	11,321
221	701	16.01.2023	XYZ	XYZ	XYZ – related party	-	11,700
1789	701	09.03.2023	XYZ	XYZ	XYZ – related party	-	131,970
1790	701	09.03.2023	XYZ	XYZ	XYZ – related party	-	131,970
3651	701	15.03.2023	XYZ	XYZ	XYZ – related party	-	1,990

Source: Author's own elaboration.

A number of questionable sales records involving a related party were identified and subjected to substantive procedures, including, inter alia, the verification of contracts and the obtaining of external confirmations. As a result of the procedures performed, the KAP identified irregularities consisting of 14 duplicate invoices and the application of an incorrect price list. The total value of irregularities in this area amounted to PLN 550,000. The KAP communicated these findings to the entity's management. The method based on Benford's Law effectively analysed highly aggregated data, thereby enhancing audit efficiency.

4. Fraud Detection Using the M-score

4.1 Characteristics of the Beneish Model

The Beneish Model stands as one of the most prominent mathematical methods for detecting financial statement fraud. It facilitates the determination of whether financial data has been manipulated or is susceptible to manipulation in the near future (Lachowski, 2019). Based on research, specific indicators were identified and specified, and assigned appropriate weights. The objective of this method is to ascertain whether the calculated values of individual components, as well as the global M-score, classify an entity as a “manipulator” or a “non-manipulator” (Kumalasari, Puspaningsih, 2023). The model’s effectiveness is contingent upon data quality; however, studies indicate its high diagnostic accuracy in identifying both manipulators and non-manipulating entities (Golec, 2019, p. 8). It is noteworthy that the model’s components incorporate the revenue cycle, the impact of which is delineated in the table below.

The Revenue Cycle in the Beneish Model

No.	Areas of Earnings Manipulation	Examples of Actions
1.	Premature revenue recognition	Recognising total revenue when performance obligations to the customer have not been satisfied, or recognising revenue despite the lack of transfer of significant risks to the customer
2.	Revenue overstatement	Manipulation of assumptions and accounting estimates

Source: Author’s own elaboration based on A. Golec, Ocena skuteczności modelu Beneisha w wykrywaniu manipulacji w sprawozdaniach finansowych [Evaluation of the Effectiveness of the Beneish Model in Detecting Financial Statement Manipulation], University of Gdańsk, Gdańsk 2019.

The literature distinguishes two variants of the Beneish Model, differing in the scope of indices employed: the 5-variable M-score and the 8-variable M-score (Lesiak, 2024, p. 3). For the purposes of this paper, the variant comprising eight indices was subjected to detailed analysis. The characteristics of the applied indices are presented in the table below.

Formulae of the Indices Comprising the 8-Index Model

Name	Formula	Justification
DSRI – Days Receivable Index	$\frac{\text{Receivables}_t / \text{Revenue}_t}{\text{Receivables}_{t-1} / \text{Revenue}_{t-1}}$	Potential for revenue overstatement
GMI – Gross Margin Index	$\frac{(\text{Revenue}_{t-1} - \text{COGS}_{t-1}) / \text{Revenue}_{t-1}}{(\text{Revenue}_t - \text{COGS}_t) / \text{Revenue}_t}$	Negative signal regarding future prospects
AQI – Asset Quality Index	$\frac{[1 - (\text{CA}_t + \text{PPE}_t - \text{Securities}_t)] / \text{Total assets}_t}{[1 - (\text{CA}_{t-1} + \text{PPE}_{t-1} + \text{Securities}_{t-1})] / \text{Total assets}_{t-1}}$	Potential for deferring costs to future periods by capitalising them on the balance sheet
SGI – Sales Growth Index	$\frac{\text{Revenue}_t}{\text{Revenue}_{t-1}}$	Pressure to sustain growth rates
DEPI – Depreciation Index	$\frac{\text{Depreciation}_{t-1} / \text{PPE}_{t-1} + \text{Depreciation}_{t-1}}{\text{Depreciation}_t / \text{PPE}_t + \text{Depreciation}_t}$	Practices aimed at inflating earnings
SGAI – SG&A Expense Index	$\frac{\text{SG\&A}_t / \text{Revenue}_t}{\text{SG\&A}_{t-1} / \text{Revenue}_{t-1}}$	Loss of control over administrative costs or excessive sales support activity
TATA – Total Accruals to Total Assets	$\frac{\text{WDK}_t - \text{PON}_t}{\text{Assets}_t}$	Significant discrepancies between net income and actual cash flows may suggest earnings management
LVGI – Leverage Growth Index	$\frac{(\text{Curr. Liabilities}_t + \text{LT Debt}_t) / \text{Total Assets}_t}{(\text{Curr. Liabilities}_{t-1} + \text{LT Debt}_{t-1}) / \text{Total Assets}_{t-1}}$	Presence of debt covenants that may incentivize manipulation

PPE – Property, Plant and Equipment

COGS – Cost of Goods Sold

CA – Current Assets

Securities – Long-term Investments

SG&A – Selling, General and Administrative Expenses

Curr. Liabilities – Current Liabilities

LT Debt – Long-term debt

Income from Cont. Ops – Income from Continuing Operations

CFO – Net Cash Flow from Operations

Source: Author's own elaboration based on A. Golec, Ocena skuteczności modelu Beneisha w wykrywaniu manipulacji w sprawozdaniach finansowych, University of Gdańsk, Gdańsk 2019.

The final equation used to determine the 8-variable M-score, taking into account the weights of individual indices (Anh, Linh, 2016, p. 6), is:

$$M\text{-score } 8 = -4,84 + 0,92 DSRI + 0,528 GMI + 0,404 AQI + 0,892 SGI + 0,115 DEPI \\ - 0,172 SGAI + 4,679 TATA - 0,327 LVGI$$

The interpretation of results involves comparing the obtained values against the model's threshold parameters. Inferences may be drawn in two ways: on the basis of the aggregate M-score value, or through the analysis of its individual components. In the present case, the updated M-score threshold of -1.78 was applied, whereby a value exceeding this threshold classifies an entity as a data manipulator, while a lower value classifies it as a non-manipulator (Beneish, Lee, Nichols, 2012, p. 11). The literature establishes an interpretive framework for each individual index, the threshold values of which are presented in the table below.

Threshold Values of Indicators in the Beneish Model

Index	Manipulator	Non-Manipulator
DSRI	1.412	1.030
GMI	1.159	1.017
AQI	1.228	1.031
SGI	1.581	1.133
DEPI	1.072	1.007
SGAI	1.107	1.085
TATA	0.049	0.015
LVGI	1.124	1.033

Source: Author's own elaboration based on Accuracy of the Beneish Model as Applied to Polish Enterprises Known to Manipulate Financial Reports, retrieved from: https://www.wir.ue.wroc.pl/docstore/download/@UEWRde51994cd20648608e7af8e62368406f/Wiszniowski_Accuracy_Of_The_Beneish_Model.pdf, (accessed: 22.12.2024).

Exceeding the threshold value assigned to the “non-manipulator” category signals an elevated risk of manipulation and indicates the need for closer examination. Beneish’s research suggests that mean values above 1.08 warrant further scrutiny, although this principle is not universal and does not apply to all indices – for SGI the threshold is 1.133, and for TATA it is 0.015 (Dalecka, 2015, p. 6).

The procedural steps for fraud detection using the M-score method are as follows:

1. Obtain input data and verify their completeness and comparability.
2. Calculate the indices using Excel spreadsheet functions in accordance with the formulae presented herein.
3. Conduct both aggregate and individual comparisons.
4. Draw conclusions.
5. Determine whether additional audit procedures are warranted.

The effectiveness of the Beneish Model is contingent upon ensuring the comparability of historical data. The resulting M-score should be treated exclusively as an indicator of the probability of manipulation, rather than as conclusive evidence of its presence or absence.

4.2 When the Numbers Don’t Add Up – The M-score Model in Practice

Entity Z is a joint-stock company operating in the small electronics sector, conducting both manufacturing activities (75 per cent of revenue) and trading activities (25 per cent). Financial reporting is conducted in accordance with Polish regulations, with no changes in accounting policy. The financial statements for the years 2022–2023 were subject to a mandatory audit. The audit for 2022 was concluded with an unmodified opinion.

In the audit plan, the Key Audit Partner (KAP) assessed the risk of material misstatement in the revenue area as high, established performance materiality at PLN 195,000, and planned the execution of the 8-variable M-score analysis. In the course of implementing the audit plan, financial data for the years 2022–2023 were obtained and subjected to verification of completeness and accuracy, including the reconciliation of comparative data, account mapping, and preliminary inspection of records. No material irregularities were identified, which enabled the M-score analysis to be performed. The KAP calculated the eight indices required to determine the M-score parameter using Excel spreadsheet functions. The results of the calculations are presented in the table below.

Results of Calculations of the M-score 8 Components

Index	Calculation Result
DSRI	1.365
GMI	0.866
AQI	1.001
SIGI	1.191
DEPI	0.963
SGAI	1.028
TATA	-0.022
LVGI	0.951

Source: Author's own elaboration.

The KAP verified the above results against the threshold values of the indices in accordance with the relevant literature. The thresholds for classifying a marker as a “manipulator” were established as follows:

- for DSRI, GMI, AQI, DEPI, SGAI, LVGI – 1.08,
- for SIGI – 1.133,
- for TATA – 0.015.

Exceeding these values results in classification as a manipulator. The comparison of results against threshold values is presented in the table below.

Comparison of Beneish Marker Calculation Results Against Threshold Values

Index	Calculation Result	Manipulator/ Non-Manipulator
DSRI	1.365	Manipulator
GMI	0.866	Non-Manipulator
AQI	1.001	Non-Manipulator
SIGI	1.191	Manipulator
DEPI	0.963	Non-Manipulator
SGAI	1.028	Non-Manipulator
TATA	-0.022	Non-Manipulator
LVGI	0.951	Non-Manipulator

Source: Author's own elaboration.

In the subsequent step, the primary parameter was calculated on the basis of the eight component indices.

$$M - \text{score}_8 = -4,84 + 0,92 * 1,365 + 0,528 * 0,866 + 0,404 * 1,001 + 0,892 * 1,191 + 0,115 * 0,963 - 0,172 * 1,028 + 4,679 * (-0,022) - 0,327 * 0,951 = -2,14$$

The KAP obtained an M-score 8 value of -2.14, which, in accordance with the adopted thresholds, indicates the absence of manipulation. Guided by professional scepticism, the KAP selected markers DSRI and SGI for further verification, as their values deviated from the reference levels. Since the financial statements for 2022 had been audited with an unmodified opinion, detailed analysis was limited to the 2023 data, with particular attention to the fact that both indices are based primarily on the relationship between revenue and receivables. The KAP performed detailed substantive tests in the aforementioned areas, including the obtaining of external confirmations in accordance with KSB 505. As a result, irregularities were identified in sales invoices, and the total value of the fraud in this area amounted to approximately PLN 415,000.

5. Challenges Facing Statutory Auditors

National Auditing Standards impose on the statutory auditor an obligation of ongoing alertness regarding fraud risk at all stages of the audit. This does not, however, imply the a priori attribution of dishonest intent to the audited entity. The key challenge remains maintaining the balance between professional scepticism and the role of the audit as an instrument supporting reliable financial reporting.

Progressive digitalisation, whilst bringing numerous benefits in terms of operational efficiency and service accessibility, simultaneously gives rise to new threats.

Concurrently, the risk of financial fraud also increases, with its scale and complexity growing in parallel with the development of modern technological solutions (Gratkowska, 2024). This necessitates the continuous development of statutory auditors' competencies and the advancement of modern analytical tools.

A significant barrier in this area remains the cost of implementing AI-based solutions. The largest audit firms already employ advanced tools (Gajdziński, 2024), whereas smaller entities – which employ the majority of statutory auditors in Poland (PANA, 2024, p. 32) – frequently lack the requisite financial resources. In this context, collaboration and integration between the PIBR and PANA professional bodies acquires particular significance, enabling economies of scale and broader access to modern technologies. Broad enquiries should be directed to external providers of highly specialised machine learning and AI services, with the resulting costs subsequently apportioned among participating statutory auditors. Access to advanced technology-based tools will render the audit market more secure. The financial sector in Poland ranks among the industries with the greatest potential to benefit from the implementation of AI-based solutions (PSI, Warsaw, 2020) – the time to seize this opportunity has come.

According to the fraud report, in the Eastern European region only 6 per cent of frauds are identified by external auditors (ACFE, 2024, p. 84). This figure gives little cause for optimism; a failure to develop technological competencies and the abandonment of efforts to advance new fraud detection tools may lead to a further diminution of audit effectiveness in protecting stakeholders.

Conclusion

The statutory auditor must demonstrate not only substantive competencies but also astuteness and the capacity to conduct a detailed analysis of the signs of fraud risk. For this reason, professional judgment and scepticism should be subject to continuous development – not merely within the framework of mandatory continuing professional education, but equally as a reflection of the profession’s high ambitions and aspirations. The rich history of the statutory audit profession attests to its enduring and timeless character. Dynamic economic changes keep this profession in a state of continuous evolution. Artificial intelligence and machine learning represent merely illustrative examples of the opportunities and threats they present.

The examples presented in this paper demonstrate that analytical methods constitute an effective instrument for responding to fraud risk. Their application not only enhances the quality of financial statement audits but also enables more efficient working practices, allowing for the verification of large datasets within a relatively short timeframe.

The research findings confirm the hypothesis advanced in this paper: that the statutory auditor plays a pivotal role in protecting enterprises and their stakeholders, and that analytical procedures effectively support fraud detection, significantly reducing the likelihood of fraud materialising.

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