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# THE BENEISH MODEL IN IDENTIFYING SIGNALS OF POTENTIAL FINANCIAL STATEMENT MANIPULATION: EVIDENCE FROM CONSTRUCTION-SECTOR COMPANIES LISTED ON THE WARSAW STOCK EXCHANGE

**Abstract**

*The article presents the principles of functioning and possible applications of Beneish's M-score model. Subsequently, it investigates whether the frequency of the model's indications of financial statement manipulation is higher for companies in the construction sector compared to companies from other industries. The study employs both a literature review and an empirical verification of the model's indications for companies operating in the construction and building materials sectors, as well as those from other industries. In total, the analysis covered 7,701 individual financial statements of companies listed on the Warsaw Stock Exchange (WSE), prepared for the years 2004–2023. The results of the analysis showed that, contrary to expectations based on the literature review, financial statement manipulation in the construction sector occurs significantly less frequently than in other industries, measured by the number of red flags identified through the five-factor Beneish model. The results suggest that greater attention should be directed toward companies outside the construction sector, where the risk of manipulation may be higher.*

**Keywords:** *M-score model, Beneish model, manipulation, fraud, financial statements, construction sector*

## Introduction

Financial statements are the final product of accounting. Their primary purpose is to provide information about an entity's activities and financial position to users such as investors, owners, lenders, business partners and customers. These users rely on financial reports when making economic decisions. The credibility of financial information is therefore one of the key conditions for the proper functioning of capital markets.

However, accounting does not provide one objective and universal set of rules that can be mechanically applied to all entities. The complexity of economic reality means that the measurement of business activities requires the application of general principles, but also involves a considerable degree of judgement and subjectivity (Staszel, 2019). This creates room for accounting choices and estimates, and in some cases also for intentional distortions of financial data.

Numerous financial scandals have shown that fraudulent financial reporting may lead to company failures, investor losses and broader financial market disruptions (Petra & Spieler, 2020). The literature increasingly emphasizes the growing importance of the credibility of financial information as a fundamental qualitative characteristic, assuming that financial statements must faithfully represent transactions and other events they aim to depict – or that users would reasonably expect them to reflect (Wójcik-Jurkiewicz, Jurkiewicz, 2014). Intentional misstatements or omissions in financial statements, made with the intention of misleading users, are commonly referred to as fraudulent financial statements (Shahana et al., 2023). One way of identifying warning signals of such practices is to use fraud prediction models. Among the most widely used tools in this area is the Beneish M-score model (Omar et al., 2014).

The construction sector has attracted particular attention in this context. Polish media have reported irregularities in financial statements and governance practices in construction companies, and accounting literature points to accounting estimates as an area especially vulnerable to manipulation (Chojnowski & Honko, 2013). Construction contracts often require long-term accounting, estimates of contract progress, future costs and expected revenues. These features suggest that construction companies may be exposed to specific financial reporting risks.

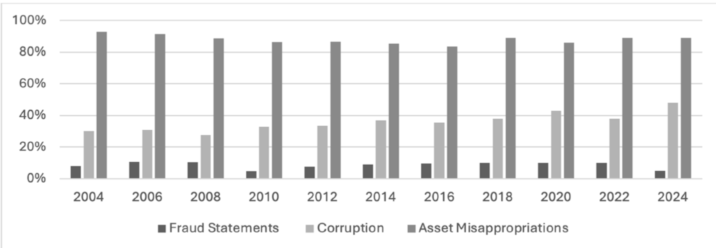
Accordingly, the article pursues three objectives. First, it presents the five-factor Beneish M-score model as a screening tool for identifying signals of potential financial statement manipulation. Second, it compares the frequency of model-based warning signals in the financial statements of construction and building-materials companies with companies from other industries listed on the Warsaw Stock Exchange. Third, it discusses the practical usefulness and limitations of such screening for investors, auditors and capital market regulators.

Based on the theoretical considerations and prior findings, the main research hypothesis assumes that publicly listed companies in the construction sector are more likely to be identified by the Beneish model as showing signals of potential financial statement manipulation than publicly listed companies from other industries. Importantly, this hypothesis refers to model-based indications, not to confirmed cases of fraud.

# Literature Review

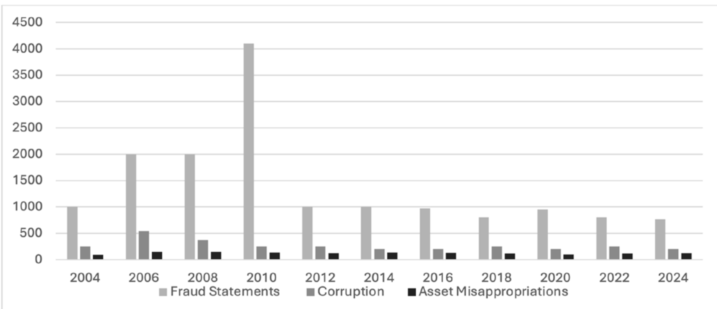
A fraudulent financial statement contains intentional misrepresentations, including omissions of amounts or failures to disclose information, with the aim of misleading users of the financial report. According to the latest report by the Association of Certified Fraud Examiners (ACFE, 2024), losses caused by detected fraud and abuse amount to millions of dollars annually, while the estimated and extrapolated damages to businesses are already in the trillions of dollars. Figures 1 and 2 present aggregated information on the scale of economic fraud and the distribution of resulting losses over the period 2004–2024, which corresponds to the time frame used in the authors' own research.

**Figure 1.** *Frequency of fraud occurrence by type in the years 2004–2024*




**Source:** own work based on ACFE, 2024.

**Figure 2.** *Amount of losses (in thousands of USD) in the years 2004–2024*




**Source:** own work based on ACFE, 2024.

An analysis of reports from the years 2004–2024 indicates that the most common type of fraud (accounting for an average of 88% of all disclosed cases) is asset misappropriation. Corruption represents, on average, 36% of all fraud cases, while financial statement fraud accounts for only a small share – an average of 9% of all recorded fraud incidents (see Figure 1).

However, when considering the amount of losses caused by each type of fraud, financial statement fraud leads to by far the largest losses, as shown in Figure 2. The average loss associated with fraudulent financial reporting is as high as USD 1.4 million, compared to USD 269,000 for corruption and only USD 123,000 for asset misappropriation.

The construction industry has long attracted the attention of researchers due to the risk of financial reporting manipulation. In the international literature, scholars frequently examine whether the construction sector is more susceptible to manipulation compared to other industries. It is often emphasized that construction is one of the sectors particularly exposed to dishonest reporting practices. Trisnanda and Surifah (2023) report that the fraud rate in this sector reaches as high as 16% of companies, placing it among the industries with the highest fraud risk levels. Similar findings were obtained in studies on Turkish SMEs, where construction companies were more likely to engage in financial data manipulation than firms from other sectors (Senvar, Hamal, 2022).

A similarly high vulnerability to manipulation is confirmed by Safta et al. (2023), who analyzed Romanian publicly listed companies and found that 100% of construction firms engaged in some form of financial manipulation. Similar results were observed in the tourism and retail sectors. The significant impact of financial fraud on the value of construction companies is also supported by Marjohan et al. (2023), whose research focused on the residential construction sector. The authors emphasize that the effectiveness of internal audits plays a crucial role in mitigating manipulation; however, during periods of economic slowdown, the risk of fraud increases considerably. In Asian countries, a high incidence of fraud in the construction industry has also been documented (Liu, Lu, 2003). Koowattanatianchai (2018) found that construction companies in Thailand frequently manipulated financial results, although the scale of such practices has declined in recent years due to stricter reporting regulations and improved corporate governance following the Asian financial crisis.

The susceptibility of the construction sector to manipulation is also supported by broader-scope studies. Saleem et al. (2024) emphasize that the high complexity of construction projects and investment-related risks make the industry particularly vulnerable to unethical practices. In their analysis of non-financial Pakistani companies using the Beneish model, it was shown that as many as 46% of firms were involved in earnings manipulation. The most affected sectors included manufacturing and raw materials industries, particularly the cement and chemical industries, which indirectly confirms the high vulnerability to manipulation in sectors closely related to construction. Similar conclusions were drawn by Budić (2023), who observed that financial fraud in the construction sector is more prevalent in developed countries, due to differences in regulatory oversight and supervision levels.

It is also worth noting that the Beneish model has been widely used to compare the scale of earnings manipulation across different sectors. For example, Kaur et al. (2014), in a study on Indian companies, identified the IT and retail sectors as the most vulnerable to manipulation. Evidence of manipulation has also been confirmed in numerous other sectors, including manufacturing and trade (Peker, 2023), agriculture, forestry, and fisheries (Durana et al., 2022), as well as the financial sector (Khatun et al., 2022). The Beneish model has been repeatedly validated in practice by evaluating its effectiveness in identifying companies as potential manipulators of financial statement data. In recent years, it has also been frequently applied in studies covering longer time horizons and focusing on publicly listed companies on European markets, including Hungary (Fenyves et al., 2023), Romania (Timofte et al., 2021), Slovakia (Baco et al., 2023), Bosnia and Herzegovina (Halilbegovic et al., 2020), and Greece (Repousis, 2016).

Three characteristics of the construction sector are especially relevant from the perspective of potential manipulation. The first is the complexity and long duration of projects, which make cost and revenue forecasts difficult. The second is discretion in contract valuation, especially when entities estimate the degree of project completion and future costs. The third is intense competition and pressure on financial performance, which may create incentives to present results in a more favorable way.

In summary, the findings of existing studies clearly indicate that the construction sector is particularly susceptible to financial manipulation. This vulnerability stems from factors such as performance pressure, project complexity, investment risk, and pressures to meet profit targets. Although in some countries the introduction of stricter regulations and improvements in corporate governance have contributed to reducing the scale of this phenomenon, there is still a lack of broader comparative studies that would allow for a definitive conclusion as to whether manipulation occurs more frequently in the construction sector than in other industries. This research gap became the main motivation for the authors to undertake an empirical study based on a large sample of financial statements of companies listed on the WSE, covering a long-term time horizon of 20 years.

## Materials and methods

The aim of the study was to examine the results generated by the Beneish model for selected companies listed on the WSE, distinguishing between those operating in the construction sector and those from other industries. The research sample included all companies listed on the WSE as of December 31, 2023, and the analysis covered all published financial statements of these companies. Financial statements were excluded if, due to missing data or other objective reasons, it was not possible to calculate any of the five model indicators (e.g., when the denominator of a given ratio equaled zero for a particular company). The analysis was conducted using data from the EMIS Notoria database. The study employed the five-factor version of the Beneish model, as numerous prior studies have confirmed its higher accuracy (Roxas, 2011; Anning, Adusei, 2020; Lehenchuk et al., 2021). Additionally, recent research conducted in the Polish economic environment has shown that the five-factor model is more effective than the original eight-factor version in detecting manipulation (Lesiak, 2024). A cutoff value of −1.78 was applied, consistent with both the original threshold proposed by the model's author and with findings from Polish studies indicating its suitability in local conditions (Golec, 2019). Each indicator exceeding its threshold was treated as a *red flag*.

Accordingly, using the five-factor Beneish model, each financial statement could be assigned between 0 and 5 red flags.

$$M5 = -6{,}065 + 0{,}823DSRI + 0{,}906GMI + 0{,}593AQI + 0{,}717SGI + 0{,}107DEPI$$

where:
*DSRI* = Days' Sales in Receivables Index,
*GMI* = Gross Margin Index,
*AQI* = Asset Quality Index,
*SGI* = Sales Growth Index,
*DEPI* = Depreciation Index.

The threshold level of the M-score has been revised several times by the model's author (Herawati, 2015). Ultimately, in 2012, M.D. Beneish adopted the cutoff point of –1.78 for identifying potential financial statement manipulation (Beneish et al., 2013). An M-score higher than –1.78 indicates that the financial statements may have been manipulated. The use of the selected indicators in the model can be interpreted as follows.

The DSRI measures whether accounts receivable and revenue (sales) remain in balance over two consecutive years. If the growth in receivables is disproportionate to the growth in sales, such a change may be interpreted as a sign of artificially inflating revenue.

$$DSRI = \frac{net\ receivables\ (t)}{sales\ (t)} / \frac{net\ receivables\ (t-1)}{sales\ (t-1)}$$

The GMI (Gross Margin Index) evaluates changes in gross profit margin between the previous and current periods. A decline in gross margin is perceived by the financial market as a negative signal regarding future profitability, which in turn reduces the efficiency of invested capital. Such a situation is associated with weaker business prospects and an increased likelihood of financial statement manipulation.

$$GMI = \frac{\text{sales (t} - 1) - \text{ cost of goods sold (t} - 1)}{\text{sales (t} - 1)} / \frac{\text{sales (t)} - \text{ cost of goods sold (t)}}{\text{sales (t)}}$$

The AQI index relates to one of the fundamental techniques of financial statement manipulation – activating costs, i.e., recording them on the balance sheet instead of recognizing them in the income statement.

$$AQI = (1 - \frac{current\ assets(\mathrm{t}) + \text{ net fixed assets(t)}}{total\ assets(\mathrm{t})})/(1 - \frac{\text{current assets(t} - 1) + \text{net fixed assets(t} - 1)}{\text{total assets(t} - 1)})$$

The SGI index measures the rate of sales growth between two consecutive periods. The Beneish model assumes that rapidly growing companies are more susceptible to financial manipulation.

$$SGI = \frac{sales\ (t)}{\text{sales (t} - 1)}$$

The DEPI index is a ratio that compares the level of depreciation in relation to fixed assets between two periods. DEPI detects whether a company is slowing down depreciation, which can artificially boost profits.

$$DEPI = \frac{\text{depreciation(t} - 1)}{\text{depreciation(t} - 1) + \text{net assets (t} - 1)} / \frac{\text{depreciation(t)}}{\text{depreciation(t)} + \text{net assets(t)}}$$

In addition to developing the model, Beneish also demonstrated that when the value of a given indicator exceeds 1.08, particular attention should be paid to that area, as it represents a so-called *red flag* – a signal that financial misstatement may have occurred (Munteanu et al., 2024).

Based on the theoretical considerations and the literature review presented, the main research hypothesis was formulated as follows: Publicly listed companies in the construction sector are more likely to manipulate data in their financial statements than publicly listed companies in other industries. For the purpose of statistical verification, two specific (sub-)hypotheses were defined:

- H1: Publicly listed companies in the construction sector are more frequently identified by the Beneish model as entities potentially engaging in financial statement manipulation than companies from other sectors.
- H2: Publicly listed companies in the construction sector receive a higher number of red flags as indicated by the Beneish model than companies from other sectors.

The Beneish probit model is considered the most widely used model in the world for detecting fraudulent financial reporting (Mahama, 2015). The model initially employed eight financial ratios, but was later reduced to five key indicators. The formula for the five-factor version of the model is as follows:

The initial verification of H1 and H2 was performed using chi-square tests, the analysis was supplemented with effect-size measures. For H1, Phi/Cramer's V, odds ratio and relative risk were calculated; for H2, Cramer's V was calculated to assess the practical magnitude of the association between sector affiliation and the number of red flags. Since the dataset consists of repeated firm-year observations, logistic regression with firm-clustered standard errors was also used as a robustness check for H1. In the regression models, the dependent variable equals 1 if the financial statement is classified by the Beneish model as potentially manipulated and 0 otherwise. The main explanatory variable identifies construction-sector companies. Additional models include year effects and firm-level controls: size, leverage and profitability.

Cramer's V was introduced because the p-value from the chi-square test does not show the strength of the association. In a large sample, even small differences may be statistically significant. Therefore, Cramer's V was used to distinguish statistical significance from practical significance. It was calculated as V = sqrt(chi-square / [N x (k – 1)]), where N is the number of observations and k is the smaller number of categories in the contingency table. Values close to 0 indicate a weak association, whereas values close to 1 indicate a strong association.

The logistic regression was estimated as a robustness check for H1. The dependent variable took the value of 1 when a financial statement was classified by the Beneish model as potentially manipulated and 0 otherwise. The key explanatory variable identified construction-sector and building-materials companies. To address the non-independence of repeated observations for the same companies, standard errors were clustered at the firm level. Four specifications were estimated: a baseline model without controls, a model with year effects, a model with firm-level controls (size, leverage and ROA) and year effects, and a model with winsorized controls and year effects.

# Results

During the empirical study, a total of 7,701 financial statements were analyzed using the Beneish model. Due to the model's characteristics, data from the preceding period was also taken into account for each financial statement in order to perform the necessary calculations.

The research sample included financial statements of companies listed on the WSE – a total of 437 companies, with data covering the years 2004 to 2023. Among them, 147 companies operated in the *construction* or *building materials* sectors, providing 1,803 financial statements, while the remaining 290 companies operated in other industries, contributing 5,898 financial statements. The total research sample of 7,701 financial statements is considered large, especially in comparison to previous empirical studies using the Beneish model on samples of WSE-listed companies. For example, Sylwestrzak (2022) analyzed financial reporting irregularities using the Beneish and Roxas models based on 110 observations from WSE-listed firms for the years 2015–2020. Golec (2019) assessed the usefulness of the Beneish model in detecting earnings management practices, analyzing a sample of 24 matched pairs of companies. Lesiak (2024) tested the model's effectiveness using ROC curves and confusion matrices on a sample of 231 financial statements from WSE-listed companies.

The first stage of the study identified which financial statements were flagged by the Beneish model as potentially manipulated and which were not. The results are presented in Table 1.

**Table 1.** *Beneish model classification by sector*

| Group | Construction Sector | | Other Industries | |
|---|---|---|---|---|
| Flagged by the Beneish model | 248 | 13,8% | 1347 | 22,8% |
| Not flagged by the Beneish model | 1 555 | 86,2% | 4 551 | 77,2% |
| Total | 1 803 | 100% | 5 898 | 100% |

**Source:** own work.

In the construction sector (1,803 financial statements), the Beneish model identified potential manipulation in only 13.8% of the statements. In contrast, among companies from other industries, the model flagged 22.8% of the statements as potentially manipulated. This percentage is almost twice as high as in the construction sector. The difference in the proportion of manipulators between the construction sector and other industries is statistically significant, as confirmed by the chi-square test, the results of which are presented in Table 2. Therefore, the research hypothesis H1 – stating that *Publicly listed companies in the construction sector are more frequently identified by the Beneish model as entities potentially manipulating financial statement data than companies from other industries* – must be rejected.

**Table 2.** *Chi-square test and effect-size measures for sector and Beneish model classification*

| | |
|---|---|
| **Chi-square ($\chi^2$) statistic** | 69,37879 |
| **p-value** | 8,1258E-17 |
| **N** | 7,701 |
| **Phi / Cramer's V** | 0.095 |
| **Odds ratio: construction sector vs. other industries** | 0.539 |
| **Relative risk: construction sector vs. other industries** | 0.602 |

**Source:** own work.

The chi-square test indicates a statistically significant relationship between sector affiliation and model-based classification. However, the effect size is small. The value of Phi/Cramer's V equals 0.095, indicating a weak association. The odds ratio of 0.539 means that the odds of being flagged by the Beneish model were approximately 46% lower for construction-sector financial statements than for financial statements from other industries. The relative risk of 0.602 indicates that the frequency of model-based indications in the construction sector was approximately 60% of that observed in other industries. Therefore, H1 is rejected with respect to model-based indications, but this result should not be interpreted as evidence of a lower confirmed incidence of fraud.

In the second stage of the empirical study, each analyzed financial statement was assessed to determine the number of red flags indicated by the individual Beneish model indicators. The financial statements were classified based on the number of red flags – from 0 to 5 – assigned to each statement, while maintaining the distinction between companies from the construction sector and those from other industries. The results of this stage are presented in Table 3.

**Table 3.** *Number of red flags in the financial statements of construction sector companies and other companies*

| Number of red flags | Construction Sector | | Other Industries | |
|---|---|---|---|---|
| 0 red flags | 206 | 11.4% | 598 | 10.1% |
| 1 red flags | 698 | 38.7% | 2080 | 35.3% |
| 2 red flags | 663 | 36.8% | 2128 | 36.1% |
| 3 red flags | 202 | 11.2% | 899 | 15.2% |
| 4 red flags | 33 | 1.8% | 176 | 3.0% |
| 5 red flags | 1 | 0.1% | 17 | 0.3% |
| Total | 1 803 | 100.0% | 5 898 | 100.0% |

**Source:** own work.

Based on the results presented, it can be observed that in the construction sector, the share of financial statements with a low number of red flags is noticeably higher. In contrast, the share of statements with a high number of red flags, indicating potential manipulation, is significantly greater among companies from other industries. This relationship again proved to be statistically significant. The results of the chi-square test are presented in Table 4.

**Table 4.** *Chi-square test and effect size for sector and number of red flags*

| | |
|---|---|
| Chi-square ($\chi^2$) statistic | 32,64968 |
| p-value | 4,4168E-06 |
| N | 7,701 |
| Cramer's V | 0.065 |

**Source:** own work.

The relationship between sector and the number of red flags is statistically significant. Nevertheless, Cramer's V equals 0.065, which indicates a very weak association. Therefore, H2 is rejected in the sense that construction-sector companies do not receive a higher number of model-based warning signals than companies from other sectors. The low effect size suggests that the practical magnitude of this sectoral difference is limited.

Because the number of red flags is an ordered count from 0 to 5, the chi-square result should be treated as a descriptive association rather than a full panel-data test. The low value of Cramer's V indicates that the practical magnitude of the sectoral difference in the distribution of red flags is very limited. Accordingly, the rejection of H2 should be interpreted only as evidence that construction-sector financial statements did not receive more model-based red flags in this sample; it should not be read as evidence of lower confirmed fraud incidence.

To address the panel nature of the dataset, a robustness analysis was conducted using logistic regression with firm-clustered standard errors. The results are summarized in Table 5 and Table 6.

**Table 5.** *Robustness check: logistic regression with firm-clustered standard errors*

| Model | Additional controls | Coefficient for construction sector | Odds ratio | p-value | N |
|---|---|---|---|---|---|
| Model 1 | None | -0.618 | 0.539 | 0.000011 | 7,701 |
| Model 2 | Year effects | -0.606 | 0.546 | 0.000018 | 7,701 |
| Model 3 | Size, leverage, ROA, year effects | -0.292 | 0.747 | 0.0312 | 7,667 |
| Model 4 | Winsorized controls, year effects | -0.276 | 0.759 | 0.0409 | 7,667 |

**Source:** own work.

**Table 6.** *Additional regression statistics: clustered standard errors and confidence intervals*

| Model | Clustered SE | Odds ratio | 95% CI for odds ratio |
|---|---|---|---|
| Model 1 | 0.141 | 0.539 | 0.409-0.710 |
| Model 2 | 0.141 | 0.546 | 0.414-0.720 |
| Model 3 | 0.136 | 0.747 | 0.573-0.974 |
| Model 4 | 0.135 | 0.759 | 0.582-0.989 |

**Source:** own work.

The logistic regression results confirm the direction of the chi-square analysis. In all specifications, the coefficient for the construction sector is negative. This means that construction-sector financial statements were less likely to be flagged by the Beneish model than financial statements from other industries. After adding firm-level controls and year effects, the magnitude of the sector coefficient decreases, but remains statistically significant at the 5% level. This suggests that part of the difference between sectors may be related to firm characteristics such as size, leverage and profitability. The results therefore strengthen the conclusion that the initial hypothesis is not supported, while also justifying cautious interpretation of the practical significance of the sector effect.

In the baseline specification, the odds ratio for the construction sector equals 0.539, which means that the odds of being flagged by the Beneish model were approximately 46% lower for construction-sector financial statements than for financial statements from other industries. After adding year effects, the odds ratio remains very similar (0.546). In the specification including firm size, leverage, ROA and year effects, the odds ratio increases to 0.747 and remains statistically significant. This indicates that the sector effect persists after controlling for selected firm characteristics, but its magnitude becomes smaller. Therefore, the regression analysis supports the rejection of H1 while confirming that the economic interpretation of the sector effect should remain cautious.

## Discussion

The results of both stages of the study indicate that there is no basis to support the main hypothesis suggesting a higher propensity for financial statement manipulation in the construction sector. The conducted analysis showed that the percentage of financial statements flagged by the Beneish model as potentially manipulated is significantly lower among construction companies (13.8%) compared to companies from other industries (22.8%). This finding is in contrast to the prevailing views presented in the existing literature.

The analysis of the number of red flags also confirmed significant differences between sectors. Construction companies were significantly more likely to show none or only a few warning indicators (0–2 red flags), whereas companies from other industries more frequently exhibited a higher number of red flags (3–5). This further reinforces the conclusion drawn from the study.

The results obtained point to the need for in-depth qualitative research into the reasons behind the lower risk of manipulation in the construction sector. It can be assumed that this is due to a number of factors, including greater oversight by investors and regulatory bodies, as well as the specific nature of the industry. Seasonality, variable profitability, and the long project execution cycle may result in reduced pressure to report high earnings, and thus less incentive to manipulate financial data. It is also typical for companies in this sector to use progress-based measurement methods to account for long-term contracts as of the balance sheet date. Although these methods allow for a certain degree of flexibility under financial reporting standards, they rely on measurable work completed and technical supervision, which may limit opportunities for manipulation. In addition, construction firms are less likely to report high development, R&D, or marketing expenses compared to companies in other industries (Konno, Itoh, 2018). The absence of such subjective and harder-to-verify costs may contribute to the fact that certain indicators used in the Beneish model less frequently exhibit abnormal values in this sector.

The conducted study aligns with the current research trend in Polish academic literature, which applies the Beneish model using data from the financial statements of publicly listed companies on the Warsaw Stock Exchange (WSE). The results of our study do not contradict previous findings that recognize the Beneish model as a tool of moderate usefulness (Lesiak, 2024; Comporek, 2020; Golec, 2019; Dalecka, 2015). In our view, the Beneish model should be treated as a predictive tool, and the outcomes of its application cannot serve as conclusive evidence of manipulation. The model's indications may include both false positives and false negatives, meaning that it can flag non-manipulated statements as suspicious and fail to detect actual manipulations.

The results of our study – showing that the Beneish model identified potential manipulation in 13.8% of financial statements from construction companies and in 22.8% of statements from companies in other industries – confirm the model's continued applicability in the Polish context. The identification of companies potentially manipulating their financial statements also opens the possibility of validating the model's effectiveness. Such validation can be carried out using data from capital market supervisory institutions (Tarjo, Herawati, 2015) or by comparing the results with auditor reports (Anh, Linh, 2016).

It is also worth noting that the results of our study – conducted on companies listed on the Warsaw Stock Exchange – indicate a lower scale of potential manipulation than that reported in numerous prior studies conducted on European markets, where the proportion of companies classified as manipulators reached 46–51% (Fenyves et al., 2023), 30–47% (Halilbegovic et al., 2020), 50% (Timofte et al., 2021), and even up to 91% (Durana et al., 2022).

# Conclusions

Based on the conducted empirical study, the hypothesis suggesting a higher propensity for financial statement manipulation in the construction sector has been rejected. The practical value of the findings is significant for investors, auditors, and capital market regulators alike. The results suggest that greater attention should be directed toward companies outside the construction sector, where the risk of manipulation may be higher. However, it should be emphasized that investors evaluating construction companies should focus their analysis on other types of risk, as a lower likelihood of manipulation does not eliminate operational risks.

Despite the general trend, construction companies with a high number of red flags should be monitored closely and treated as exceptions requiring in-depth analysis. Importantly, many auditors already incorporate the Beneish model into their standard risk assessment procedures. Regulators may support or recommend the use of the Beneish model by supervisory institutions, for example, in the process of risk analysis of listed companies. It is also important to promote awareness that not all industries are equally exposed to manipulation, which may help improve the quality of investment decisions and reduce bias against certain sectors of the economy.

The study has several limitations. It relies exclusively on the five-factor Beneish model, which identifies potential warning signals rather than confirmed fraud. The results have not been externally validated using regulatory sanctions, restatements, auditor opinions or court cases. In addition, although the robustness analysis accounts for repeated observations, the dataset still reflects the structure and availability of data for companies listed on the Warsaw Stock Exchange. Finally, sector affiliation alone explains only a small part of the variation in model-based warning signals. Although the additional regression analysis accounts for repeated firm-year observations by clustering standard errors at the firm level, future research may extend this approach by applying full panel models or mixed-effects specifications.

Future research should apply alternative fraud-detection models, such as the Dechow model and other accrual-based measures, and compare them with the Beneish model. Further studies should also include qualitative analysis of companies with high M-scores, external validation using confirmed cases of irregularities, and sectoral analyses that distinguish between construction companies and building-materials producers. Research should also consider macroeconomic periods, such as crisis and non-crisis years, to determine whether the frequency of red flags changes across the economic cycle.

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