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Use of Beneish M-Score: Case Study in the Spanish Fishing Sector

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ABSTRACT

The manipulation of financial statements is a practice used by companies to obtain illicit benefits or advantages over competitors. One of the world's largest bluefin tuna exporters is implicated in an alleged fraud case and accused of committing multiple crimes, including offenses against public safety and money laundering. This study analyzes the company's likelihood of fraud using the Beneish method, which detected potential accounting irregularities in five of the eight years examined (2015–2022). The findings appear to corroborate the fraud allegations against the company.

1. Introduction

The capture of bluefin tuna is one of the main activities of the Spanish fishing sector, and this species is one of the most demanded by consumers [1]. Spain is the largest producer of tuna in Europe, with its catches representing more than half of all tuna caught in Europe [2]. This highlights the fact that consumers show a strong preference for bluefin tuna based on various reasons, including its characteristic and at the same time attractive reddish hue. This has led several companies to inject additives into cheaper tuna species to pass them off as bluefin tuna and thus obtain higher profits from their sale [3]. This situation was exposed in 2018 when numerous cases of poisoning due to the consumption of adulterated tuna were reported in Spain. In addition to the health risks posed by the ingestion of tuna modified by additives, this practice also constitutes commercial fraud due to the sale of a product that is actually cheaper at a higher price [4].

A major bluefin tuna exporting company in the world is located in Spain, which has been accused of engaging in this type of activity to increase its profits through illegal bluefin tuna fishing, storing it in a secret warehouse, falsifying the relevant documentation to legalize it, adding substances to enhance the characteristic red color of this spice and delay its putrefaction, and laundering the profits

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derived from its sale on the black market [5]. The discovery of this alleged plot occurred with the so-called Operation Tarantelo, aimed at gathering evidence against companies suspected of fraud, and the judicial investigation began in January 2019 [6].

One of the crimes allegedly committed by the Spanish company that is the subject of this article, money laundering, would have been carried out through altering financial statements. According to a report published by the Association of Certified Fraud Examiners [7], between January 2022 and September 2023, fraud between January 2022 and September 2023 resulted in global losses in excess of $3.1 trillion, with a total of 1921 recorded cases and a loss of 5% of revenue for companies on an annual basis, a situation that makes the detection of these practices a matter of great importance.

In terms of who usually commits this type of crime, 41% are employees, although frauds committed at executive levels are the most damaging according to the ACFE, which structures accounting manipulation in three clearly differentiated categories: misappropriation of assets (86%), falsification of financial statements (10%) and corruption (4%), with the second category being the costliest despite its lower incidence compared to the first. According to data provided by the ACFE, the misrepresentation of financial statements causes losses of up to $39,800 per month, while corruption cases (including bribery and extortion) constitute a monthly economic loss of $11,100 [7].

This study has been designed with the view to fulfilling the pressing need to discover and deter illegal action in large economic industries such as fisheries. The implications of such fraud extend well beyond finance, actually impacting public health, sustainability of the environment, and consumer confidence. The case study is of one of Europe's highest-profile bluefin tuna exporting companies. It is a case of accounting manipulation as a means of hiding illicit business practices like illegal fishing, food contamination, and money laundering. The case points out the necessity for strong analytical tools to detect early warning signs of financial fraud.

From a learning and practical standpoint, the study is worthy of the contribution it gives to the field of forensic accounting by applying the Beneish M-Score model in a relatively untapped industry setting, e.g., the fishing industry. The study greatly contributes to the field of detecting accounting fraud by delivering valuable empirical evidence that will inform the work of regulators, auditors, and policymakers. The research outcomes, based on comparison of the results of the tested company with the results of other companies in the same sphere, allow to determine the patterns of financial behavior as a basis for further investigation and audit.

The motivation for this study is to determine the likelihood of one of the largest bluefin tuna exporting companies in Spain engaging in accounting manipulation techniques. This is being conducted as part of a judicial investigation into economic fraud and public health crimes. To achieve this, the Beneish M-Score model is employed to analyze the firm's accounts from 2015 to 2022 to identify any potential alteration in its accounts. Besides, the results obtained are compared with the results for three other companies operating within the same industry. This enables one to develop a comparison framework and to affirm the applicability of the model in real-life scenarios. This analysis is not only aimed at determining fraud indicators but to assist in developing forensic audit methods that can be applied in strategic sectors such as the food industry, where consumer safety and financial integrity are interconnected.

This research is advantageous academically and practically on a grand scale. The study is addressing detection of accounting fraud within a strategic sector like the fishing sector—specifically, the bluefin tuna sector in Spain—using rigorous and applied research methods. Firstly, the study provides meaningful empirical data on the efficacy of employing the Beneish M-Score model as a forensic technique in the identification of probable manipulations of unlisted companies' financial reports. Its application is especially meaningful where accounting fraud can be linked to larger-scale crimes such as illicit fishing, money laundering, and food product adulteration marketing, and where public health and environmental sustainability are directly affected. Furthermore, the study significantly helps progress methodology in forensic accounting. This is done by way of implementing and experimenting a quantitative model within a fairly new sectoral setting, such as industrial fishing. It allows for comparisons with the outcome of other firms doing business in the same sector, thus allowing for the establishment of patterns of financial behavior that can be utilized as a reference during future audits, court investigations, and policy development by regulatory authorities. The findings of the research offer significant contributions to control agencies, external auditors, and public policymakers since they show how financial analysis can serve as a foundation for subsequent audits, judicial reviews, and regulatory actions.

The article is structured as follows. The second section presents a brief analysis of the importance of bluefin tuna production in Spain and the fraud committed with this species. The third section presents the company under study and its current status. The fourth section presents the methodology to be used (Beneish model) to identify whether there is a possibility of misrepresentation in the accounts of the company under study. The fifth section presents and describes the results. Finally, the sixth section presents the conclusions.

2. Methodology

2.1 Case study

2.1.1 Fraud in the bluefin tuna trade

Bluefin tuna fishing represents 1.9% of the total catch at the European level and up to 6.6% of the total aquaculture production in terms of economic output [8]. Looking at data from European Union fish markets for the same year, the average level of fish consumption within the EU was 23.28 kg live weight per person per year, with bluefin tuna accounting for 3.06 kg [9]. In Spain, available information shows that fish consumption, including tuna, is an important part of the national diet, with bluefin tuna representing the species with the highest production along with sea bass. The country has 53 pole-and-line tuna vessels in the Canary Islands (Spain) and 17 tuna seiners in the Atlantic, Indian, and Pacific oceans [10].

Spain holds first place at the European level in tuna fishing volume, with approximately 70% of the EU-27 catches in the area being made by Spain and most of the rest by France [11]. Moreover, almost a third of the total catch in Spain is exported as frozen product to a large number of countries around the world, while Spain imports it from various geographical locations, mainly in South America (Table 1). At the global level, where the tuna catch reaches 5 million tons, Spain ranks seventh, surpassed by Indonesia, Japan, Taiwan, Ecuador, South Korea, and the United States. However, it is the second largest producer of canned tuna in the world, with a figure of 250,000 tons, an amount close to that of the first producer, Thailand [12].

Table 1
Spain’s exports and imports of frozen tuna in 2016. Source: Own elaboration from EUMOFA (2022)

Spanish imports of frozen whole tuna						
Frozen Whole Tuna	2009	2010	2011	2012	2013	2014
Import value (1,000 €)	86,437	89,930	90,471	129,985	128,016	72,645
Import tonnes	66,034	55,558	49,078	56,077	53,912	35,733
Spanish exports of frozen whole tuna						
Frozen Whole Tuna	2009	2010	2011	2012	2013	2014
Export tonnes	86,597	76,589	64,158	74,144	70,898	53,757
Export value (1,000 €)	105,311	110,156	108,769	161,152	157,274	97,395

Table 1
Continued

Spanish imports of frozen whole tuna						
Frozen Whole Tuna	2015	2016	2017	2018	2019	2020
Import value (1,000 €)	53,849	60,253	81,945	40,685	40,273	2,894
Import tonnes	31,517	30,679	36,496	19,064	19,213	1,362
Spanish exports of frozen whole tuna						
Frozen Whole Tuna	2015	2016	2017	2018	2019	2020
Export tonnes	60,874	60,253	81,945	40,685	40,273	2,895
Export value (1,000 €)	92,904	30,677	36,496	19,064	19,213	1,362

Given these data, food fraud in the marketing of bluefin tuna could lead to major health issues. In general, consumers show a preference to pay more money for certain products, such as bluefin tuna, for a variety of reasons, including its high culinary quality, although one of the most important reasons is its characteristic reddish color [13]. Based on the importance of this product, the European Union has detected the alteration of tuna using different methods, including the addition of nitrites, carbon monoxide, and vegetable extracts [14]. In Spain, an audit was conducted in 2017 by the European Commission due to the existence of several cases of food poisoning resulting from the consumption of spoiled fish adulterated with beet extract, according to studies conducted by food safety inspectors [15]. In total, 154 cases of poisoning were detected, in which the affected persons showed symptoms such as facial sweating, nausea, vomiting, and headaches. Despite the fact that their evolution was favorable and, therefore, did not represent a serious health problem, it did constitute commercial fraud as well as incorrect handling of the product, which was detrimental to the image of the Spanish tuna sector abroad [16].

The use of methods to adulterate tuna is carried out for two reasons: to improve the visual appearance of meat in poor condition and to vary the hue to increase the price of cheap tuna species [3]. In the second case, it was detected that the color change was induced by high doses of additives, mainly antioxidants, which prolong the shelf life of food by delaying putrefaction caused by oxidation, which generates rancidity of fats and color changes. Some additives are however allowed in the fish sector under Regulation (EC) No. 1333/2008 on food additives, such as ascorbates and citrates, E-300 (ascorbic acid), E-301 (sodium ascorbate), E-302 (calcium ascorbate), E-330 (citric acid), and E-331, E-332 and E-333 (citrates), although it should be noted that these substances must be used in appropriate doses (quantum satis) [17]. This led to several producers using very high concentrations of these additives in tuna loins, which consequently caused chromatic alterations that were very attractive to the consumer, as well as a false freshness that allowed them to be exposed to the public for prolonged periods [18]. Despite there being no limit for the use of the substances mentioned above, there is a limit for histamine, an imidazole amine commonly present in adulterated tuna; the concentrations detected were between 2500 and 3000 ppm, which constitutes a high risk since from 500 ppm it is believed that symptoms of intoxication can occur in sensitive consumers, while 1000 ppm or more is considered safe intoxication, being between 100 and 200 ppm the limit established by the European Union [19].

To address this issue, a multitude of analytical approaches have been developed to detect adulterated tuna samples, such as gas chromatography [20], spectroscopy [21], proteomics [22], and infrared spectroscopy [23]. In addition, genetic-based approaches, such as polymerase chain reaction (PCR), have shown great efficacy in detecting these practices [24]. Similarly, image processing-based examinations have been applied in the field of food science and analysis; various traits of interest, such as hue and texture, can be extracted from images using software, while damage can be detected with X-rays [25] and alteration of food matrices with smartphone-based technology [26], all of which are aimed at putting an end to food fraud not only of bluefin tuna but also of any species intended for human consumption.

2.1.2 Spanish case study company

The Spanish case study company was founded in 1984. In 1996, the company underwent a major change with the opening of a bluefin tuna fattening farm located approximately 20 km from Cartagena, whose production was destined for the Japanese market. By 2003, the company was catching 16,000 tons of bluefin tuna annually, which is practically half of all bluefin tuna fished in the Mediterranean, whose annual fishing quota amounts to 36,000 tons [27]. The following year, in 2004, the company proceeded to install two fish processing plants: one dedicated exclusively to tuna, unique in all of Europe, and the other for the production of salted and smoked fish, with a refrigeration plant of 55,700 cubic meters, 4,600 at a temperature of -140 °F [28].

Fig. 1. Location of subsidiaries of the Spanish case study company in 2022. Source: Own elaboration

Since the opening of the fattening farm, this company has experienced considerable growth, which has led to its presence in important parts of Spain, such as Canarias, and in several European countries (Figure 1). By 2022, the company held the leadership in the production of Atlantic bluefin tuna in Europe, both traps and fattening, although since 2018, the company has been dragging problems linked, among others, to public health and money laundering that have tarnished its image.

The investigation was carried out by the Central Operational Environmental Unit (UCOMA) of the Spanish security forces and Europol, whose completion took place in the summer of 2018 and is known as *Operacion Tarantelo* (Ministerio para la Transición Ecológica y el Reto Demográfico, 2024; García, 2019). *Operation Tarantelo* constitutes the largest operation carried out in Spain against the sale of bluefin tuna on the black market, a plot integrated by several companies that would be headed by the study company, and whose judicial instruction phase began in January 2019 (García, 2019). In 2018, the Justice Court of Picassent (Valencia, Spain) arrested several dozen people in up to six regions of Spain due to the commercialization of fish under poor conditions [29]. The number of people involved in the scheme amounted to 90 individuals and 29 legal entities present in 12 provinces in Spain and other countries: Portugal, Malta, France, Morocco, Tunisia, and Turkey [30].

The charges against the alleged culprits include crimes against public health, false documentation, crimes against wildlife, crimes against consumer rights, discovery and disclosure of secrets, money laundering, and participation in a criminal organization. The modus operandi involved an extensive network of companies belonging to the fishing and distribution sector that proceeded to import bluefin tuna from Italy and Malta, which was not declared and then sold using false documents in both the Spanish and foreign markets, which would have involved the purchase by land and air of approximately 1,250 tons legally and 2,500 tons illegally, amounts that would have generated an estimated annual income of €25 million in black money [31].

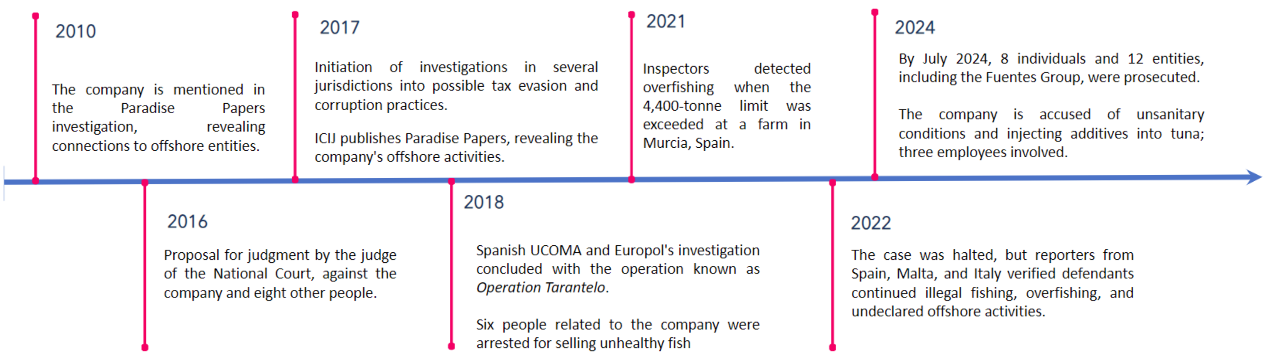

Fig. 2. The most important facts in the fraud case. Source: Own elaboration

The problem of overfishing was detected in June 2021, when inspectors from the Ministry of Fisheries inspectors warned that the 4,400 tons of the farm located in Murcia (Spain) had been exceeded, which caused the release of 1,200 tons of bluefin tuna. This represented a miscalculation of 27%, more than five times the authorized amount according to the regulations of the International Commission for the Conservation of Atlantic Tunas (ICCAT), whose limit is 5% [5].

By July 2024, a total of eight individuals and 12 legal entities had been indicted, including the Spanish company studied, accused of not meeting minimum health conditions in their facilities and injecting additives into the tuna to give them a false appearance of freshness (Figure 2). In addition, the existence of a secret warehouse in which, without any type of permit from the competent administrations, they operated without sanitary controls and in deficient sanitary conditions was accredite [32].

2.2 Method

2.2.1 *Beneish M-Score model*

In this study, the accounts of the Spanish case study company were valued to determine the possible existence of adulterated financial statements. The calculations performed on this company and three other companies in the Spanish tuna sector with which a comparison has been made were carried out using the Beneish model. The indexes used are Day's sales in receivables index (DSRI), Gross margin index (GMI), Asset Quality Index (AQI), Sales growth index (SGI), Depreciation Index (DEPI), Sales, general and administrative expenses index (SGAI), Leverage Ratio (LVGI), and the Total accruals to total assets (TATA) (Table 2).

To arrive at the final estimate, Beneish (1999) relied on a weighted maximum likelihood exogenous sample probit (WESML) and an unweighted probit model. The results obtained from the unweighted probit estimates were applied in this equation representing the Beneish model of eight variables:

$$M= -4.84+0.92*(DSRI)+0.528*(GMI)+0.404*(AQI)+0.892*(SGI) +0.115*(DEPI)-0.172*(SGAI)+4.679*(TATA)-0.327*(LVGI) \quad (1)$$

The five-variable version of the Beneish model is calculated through the following equation:

$$M= -6.065+0.823*(DSRI)+0.906*(GMI)+0.593*(AQI)+0.717*(SGI) +0.107*(DEPI) \quad (2)$$

Table 2
Indicators used in the Beneish M-Score model to detect earnings manipulation. Source: Own elaboration

Indicator	Target value
$DSRI = \frac{Receivables_t/Sales_t}{Receivables_{t-1}/Sales_{t-1}}$	*< 1*
$GMI = \frac{(Sales_{t-1} - Cost\ of\ goods\ sold_{t-1})/Sales_{t-1}}{Sales_t - Cost\ of\ goods\ sold_t/Sales_t}$	*< 1*
$AQI = \frac{1 - (Current\ assets_t + PP\&E_t)/Total\ assets_t}{1 - (Current\ assets_{t-1} + PP\&E_{t-1})/Total\ assets_{t-1}}$	*< 1*
$SGI = \frac{Sales_t}{Sales_{t-1}}$	*< 1*
$DEPI = \frac{Depreciation_{t-1}/(Depreciation_{t-1} + PP\&E_{\ t-1})}{Depreciation_t/(Depreciation_t + PP\&E_{\ t})}$	*< 1*
$SGAI = \frac{Sales,\ general\ and\ administrative\ exp\,e\,nse_t/Sales_t}{Sales,\ general\ and\ administrative\ exp\,e\,nse_{t-1}/Sales_{t-1}}$	*< 1*
$LVGI = \frac{(LTD_t + Current\ liabilities_t)/Total\ assets_t}{(LTD_{t-1} + Current\ liabilities_{t-1})/Total\ assets_{t-1}}$	*< 1*
$TATA = \frac{\Delta Working\ capital - \Delta Cash - Depreciation_t}{Total\ assets_t}$	*= 1*

In addition, in order to determine whether there is sufficient evidence to detect FFR, the following null hypotheses have been created:

H0(1A): The variables associated with the eight factors of the Beneish model would not be effective in detecting fraudulent financial reporting of the Spanish case study company.

H0(1B): The variables associated with the five factors of the Beneish model would not be effective in detecting fraudulent financial reporting of the Spanish case study company.

2.2.2 Altman's Z-Score Model

The Altman Z-Score model was developed by Edward I. Altman in 1968 as a statistical tool to predict the probability of business failure, using a technique called multivariate discriminant analysis (MDA). MDA was introduced by Ronald Fisher in 1936, which allows for observation classification in mutually exclusive groups based on a linear combination of independent variables.

Altman's study involved the use of this method to examine a sample of U.S. companies, consisting of both solvent and bankrupt firms. The researcher identified five primary financial indicators, out of More than 22 ratios. These indicators were selected based on their ability to distinguish firms that are successful from firms that are at a heightened risk of failure. The outcome was a formula that represents these ratios into one number, the Z-Score. This indicator allows categorization of companies regarding financial risk.

Taking into account the value of the indicators (Table 3), the original Altman Z-Score model is expressed by the following formula:

$$Z = 1.2*X_1+1.4*X_2+3.3*X_3+0.6*X_4+1.0*X_5 \quad (3)$$

The Z-Score value allows companies to be classified into three financial risk zones:

i. Z > 2.67: Safe zone ("safe zone"), where the probability of bankruptcy is low.
ii. 1.81 < Z < 2.67: Grey zone, indicating uncertainty and moderate risk.
iii. Z < 1.81: Distress zone, where there is a high probability of insolvency.

This helps identify companies that might have financial problems as well as those that are doing well. To make sure the model was valid, we created a second null hypothesis.

Table 3
Indicators used in the Altman's Z-Score Model to detect earnings manipulation. Source: Own elaboration

Indicator
$x_1 = \frac{\textbf{Working capital}}{\textbf{Total assets}}$
$x_2 = \frac{\textbf{Retained earnings}}{\textbf{Total assets}}$
$x_3 = \frac{\textbf{EBIT}}{\textbf{Total assets}}$
$x_4 = \frac{\textbf{Market value of equity}}{\textbf{Total liabilities}}$
$x_5 = \frac{\textbf{Sales}}{\textbf{Total assets}}$

H0(2): The Altman model's five factors wouldn't be useful in identifying the Spanish company's fraudulent financial reporting.

We tested both the first and second hypotheses. But it was also necessary to evaluate how well the financial indicators used in both models worked. We had to see if they could detect when financial reports were fake. So, a third null hypothesis was proposed:

H0(3): The indicators used in the Beneish (M-score) and Altman (Z-score) models are not enough to detect FFR.

3. Results

The results obtained from the analysis of companies between 2012 and 2021 show significant patterns in the detection of financial fraud, using the Beneish M-score and Altman Z-score models. A detailed analysis of the findings, which align with the stated null hypotheses, is provided below.

3.1 Beneish M-score model results

The M-score values, whether looking at the eight-variable or five-variable versions, show some significant ups and downs throughout the period we’re examining. In particular, the years 2014, 2016, and 2020 had values that were close to or even surpassed the -2.22 mark, which suggests a greater chance of accounting manipulation (Table 4). For example, in 2014, the M-score with eight variables was -1.87, and in 2020, it was -1.17—both above that critical threshold, hinting at the possibility of financial fraud. The analysis of individual variables reinforces this conclusion, and further analysis is needed to determine the implications of these findings. Indicators such as DSRI far exceed the average values of non-manipulator companies. In 2016, DSRI was 1.72. In 2020, it was 2.44. In 2017, the GMI stood at 2.43, but by 2021, it had dropped to 1.94. On the other hand, SGI significantly outperformed the average figures for companies that don’t manipulate their data, reaching 4.18 in 2021. These numbers hint at some irregularities in revenue, profit margins, and sales growth. Moreover, the DEPI index has been consistently high for several years, which could suggest that there have been some accounting tweaks related to depreciation to boost profits.

Given these findings, we reject the null hypothesis H0(1A). Hypothesis H0(1B) is also dismissed, as the five-variable model showed sensitivity to potential manipulations, especially in the years 2014, 2016, and 2020.

Table 4
Beneish M-Score for Spanish case study company's 2012–2018 financial statements. Source: Own elaboration

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
DSRI (Days' Sales in Receivables Index)	0.6697	1.7033	3.6133	1.4357	1.7205	0.2244	1.0853	0.5632	2.4474	0.1540
GMI (Gross Margin Index)	0.9249	0.7285	1.0051	1.0842	1.3281	2.4362	0.9514	1.8723	0.4684	1.9408
AQI (Asset Quality Index)	1.0248	1.0242	1.0623	0.9646	1.0291	0.9886	0.9224	0.9736	1.0148	0.9692
SGI (Sales Growth Index)	1.1033	0.8605	0.7470	1.1696	0.7627	3.6113	1.5041	1.5783	0.3315	4.1877
DEPI (Depreciation Index)	1.3671	1.4757	1.3162	0.9491	0.9299	0.7582	0.9780	0.7708	0.9900	0.8150
SGAI (SG&A Expenses Index)	0.9075	1.2450	1.1742	0.9100	1.3493	0.2654	0.9149	0.6331	3.0170	0.3860
LVGI (Leverage Index)	0.9427	0.9341	0.9071	0.8936	0.9714	0.9623	1.1094	1.0041	0.8622	1.0498
TATA (Total Accruals to Total Assets)	-0.0059	-0.0139	0.0014	-0.0097	-0.0039	-0.0192	-0.0056	0.0046	0.0847	0.0676
M-Score (8 var)	-3.26	-2.19	-1.87	-3.13	-2.47	-3.42	-3.34	-2.83	-1.17	-2.47
M-Score (5 var)	-4.31	-3.01	-2.56	-3.88	-3.47	-2.51	-3.94	-3.39	-2.01	-2.38

3.2 Altman Z-score model results

The Altman Z-score model has shown a steady increase in Z-index values over the years, with scores surpassing 2.67 starting in 2014, which means these companies were in the "safe zone." For example, the scores rose from 4.14 in 2020 to 4.17 in 2021. This data indicates that, from a financial stability perspective, these companies weren't facing any immediate bankruptcy risks.

Reflecting on the individual variables there certainly are some red flags. For instance, the X1 variable, which is the working capital/total assets ratio, had a negative value (-0.0236) in 2014 suggesting the firm was perhaps struggling with liquidity. In addition, X3 (EBIT/total assets) also had a negative value (-0.0112) in 2015 suggesting the firm was struggling operationally. Given that some of the individual variables provided warning signs although the Z-score model was unable to predict where fraud might occur in the years the M-score did predict fraud, while not denying that Altman did provide a valuable way to determine a company's overall financial health, it could not account for accounting fraud. In fairness, all five variables used were statistically significant ($p < 0.05$) in all cases to enable the conclusion that null hypothesis H0(2): The five-factor variables of the Altman Z-score are not adequate to detect fraud efficiently in Spanish case study company (Table 5).

Table 5
Spanish case study company : 2012–2018 Altman Z-scores. Source: Own elaboration

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
x1 Working Capital/Total Assets	0.0870	0.0356	-0.0236	0.0997	0.0126	0.0401	0.0400	0.0504	0.0745	0.0961
x2 Retained Earnings/ Total Assets	0.6483	0.6526	0.6995	0.6799	0.6821	0.7172	0.7556	0.7556	0.7892	0.7456
x3 EBIT/Total Assets	0.0307	0.0528	0.0543	-0.0112	0.0882	0.0284	0.0738	0.0706	0.1143	0.1039
x4 M.V. of Equity/Total Liabilities	2.20	2.42	2.74	3.04	3.17	3.01	3.07	3.09	3.78	3.56
x5 Sales/ Total Assets	0.0790	0.0698	0.0536	0.0667	0.1322	0.1780	0.2386	0.3311	0.1221	0.4536
Z-Score	2.63	2.84	2.99	2.77	3.34	3.26	3.55	3.61	4.14	4.17

3.3 Comparative statistical analysis

The variables in both models were exhaustively quantitatively analyzed using the statistical form of t-tests and p-values. The results show that all variables are statistically significant at the 0.05 level, reinforcing the power of the Beneish and Altman models in identifying unusual financial events (Table 6).

The findings from the Beneish model, which was statistically significant, also identified that the variables GMI ($p < 0.0005$), AQI ($p < 0.0001$) and DEPI ($p < 0.0001$) were particularly important. In the Altman model, we found that X2 (retained earnings/assets) and X4 (market value/liabilities) to be statistically significant ($p = 0.0015$ and $p = 0.0003$ respectively).

This allows us to reject the null hypothesis H0(3): The ratios we used in Beneish (M-score) and Altman (Z-score) model are not useful in FFR detection. While the methods employed differ, both models present practical tools for detecting financial fraud.

Table 6
Beneish and Altman analyses: Statistical properties. Source: Own elaboration

Variable	Mean value	SD	t-stat	p-value (aprox.)
Beneish analyses				
DSRI	1.2016	0.9645	3.94	0.0035
GMI	1.174	0.5913	6.27	<0.0005
AQI	0.9902	0.0454	68.9	<0.0001
SGI	1.4876	1.1043	4.25	0.0023
DEPI	1.1396	0.2735	13.2	<0.0001
SGAI	1.0809	0.8084	4.21	0.0024
LVGI	0.9647	0.0893	34.1	<0.0001
TATA	0.0395	0.0383	3.26	0.01
Altman analyses				
X1	0.0517	0.0386	4.23	0.0023
X2	0.7126	0.0453	49.7	0.0015
X3	0.0616	0.0386	5.05	0.0011
X4	2.908	0.47	19.6	0.0003
X5	0.1725	0.1223	4.46	0.0018

4. Conclusions

This study has demonstrated the usefulness of the Beneish M-Score model for the detection of possible accounting manipulations. Specifically, its effectiveness has been tested in one of the main bluefin tuna exporting companies in Spain. The results show that in five of the eight years analyzed (2014, 2016, 2017, 2020 and 2021) the M-Score exceeded the critical threshold of -2.22. This indicates a high probability of accounting fraud. For example, in 2020, the M-Score of eight variables reached a value of -1.17, and in 2014 it was -1.87, both above the alert threshold. In addition, individual indicators such as DSRI (2.44 in 2020) and SGI (4.18 in 2021) showed significantly higher values than those of non-manipulating companies. This fact reinforces the hypothesis of alteration of financial statements.

The Altman Z-Score model grouped the company in safe zone throughout the analyzed period. The indicators for 2012 and 2021 show this (2.63 and 4.17, respectively). While this model did not detect any outright indicators of fraud, it did show weakness in several variables. These variables include working capital over total assets (X1), which was negative in 2014 (0.0236), and EBIT over total assets (X3), which was also negative in 2015 (0.0112). Therefore, these indicators could suggest that the company had liquidity and profitability problems for these years.

By applying both models together, we have been able, on the one hand, to identify patterns of anomalous financial behavior and, on the other hand, to show that the Beneish M-Score is also useful as a tool for non-traditional industries, including fishing. This is an important contribution to forensic accounting. This is especially true for industries where accounting fraud is linked to serious crimes such as illegal fishing, money laundering and the selling of adulterated products.

This research indicates several promising directions for the detection of financial fraud. One of these is bringing hybrid models together, which combine the Beneish M-Score with artificial intelligence methods, such as neural networks or supervised learning algorithms. These methods will enhance the accuracy of detecting accounting fraud. The Beneish M-Score provides a systematic screen of financial statements of companies across various industrial categories, and is especially useful for screening the meat and dairy industries because it helps provide assurance that the product is genuine and safe to eat. Another intriguing aspect is to compare various forensic models (e.g., Beneish vs. Altman vs. F-Score vs. machine learning models) to ensure that the right model is selected for the right situation. Finally, the use of automated financial analysis to form early warning systems, which would allow regulators and auditors to investigate problems as soon as they appear, is also suggested. These types of research initiatives which are designed to improve the financial control mechanisms available, and provide greater consumer protections against businesses who wish to defraud consumers or provide inferior quality products will be useful along the way.

Author Contributions

Conceptualization, R.F-G., P.C.P, and F.P-G.; methodology, R.F-G., P.C.P.; software, R.F-G., D.P.; validation, R.F-G., F.P-G. and P.C.P.; formal analysis, R.F-G., D.P.; investigation, R.F-G., P.C.P.; resources, R.F-G.; data curation, R.F-G, P.C.P.; writing—original draft preparation, R.F-G.; writing—review and editing, R.F-G, D.P.; visualization, R.F-G., D.P.; supervision, R.F-G., D.P.; project administration, R.F-G., P.C.P.; funding acquisition, F.P-G. All authors have read and agreed to the published version of this manuscript.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author, R.F-G., upon reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that may have influenced the work reported in this study.

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