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EARNINGS MANIPULATION IN FOOTBALL CLUBS: AN INTERNATIONAL ANALYSIS

FUTBOL KULÜPLERİNDE KAZANÇ MANİPÜLASYONU: ULUSLARARASI BİR ANALİZ

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ÖZ: Bu araştırma, Avrupa'daki futbol kulüplerinde kazanç manipülasyonu riskini uluslararası karşılaştırmalı olarak incelemeyi hedeflemiştir. Bu bağlamda Avrupa Futbol Federasyonları Birliği'ne (UEFA) bağlı 9 ulusal futbol liginden, pay senetleri borsada işlem gören 18 kulübün 2018-2024 yılları arasındaki finansal verileri Beneish M-Skoru modeliyle analiz edilmiştir. Araştırmada toplam 126 kulüp-yıl gözlemi yapılmış, M-Skorları ve sekiz finansal değişken üzerinden manipülasyon riski değerlendirilmiştir. Bulgular, gözlemlerin %42'sinde manipülasyon riski olduğunu ve en yüksek riskin 2018 yılında ortaya çıktığını göstermiştir. En çok manipülasyon yapılan değişkenin SGAI, en az manipülasyon yapılan değişkenin ise GMI olduğu saptanmıştır. Özet istatistik sonuçları tüm örneklemde DSRI, SGAI ve TATA gibi değişkenlerin manipülasyon riskine daha yatkın değişkenler olduğunu buna karşın DEPI, LVGI ve AQI gibi değişkenlerin daha az volatilite ve manipülasyon eğilimi sergilediğini ortaya koymuştur. Manipülatör ve non manipülatör gruplar arasında DSRI, GMI ve TATA'da farklar bulunurken, AQI, SGI ve DEPI'de farklar sınırlı kalmıştır. Bu sonuç, manipülasyonun satış/idari giderler, alacak yönetimi ve tahakkuklarda yoğunlaştığını göstermektedir.

Anahtar Kelimeler* : *Kazanç Manipülasyonu, Kazanç Yönetimi, Beneish M Skoru, Futbol Kulüpleri, Avrupa Futbol Federasyonları Birliği.

ABSTRACT: The present study has been designed to examine the risk of earnings manipulation in European football clubs in an international comparative perspective. To this end, the financial data of 18 listed clubs from 9 national football leagues affiliated to the Union of European Football Associations (UEFA) between 2018 and 2024 were analyzed with the Beneish M-Score model. The study encompassed a total of 126 club-year observations, utilizing M-Scores and eight financial variables to assess the risk of earnings manipulation. The findings indicated that 42% of the observations exhibited manipulation risk, with the highest risk occurring in 2018. The variable SGAI was identified as the most susceptible to manipulation, while GMI was found to be the least vulnerable. The descriptive statistics demonstrate that variables such as DSRI, SGAI and TATA are more susceptible to manipulation risk in the overall sample, while variables such as DEPI, LVGI and AQI exhibit reduced volatility and manipulation tendency. Differences between the manipulator and non-manipulator groups were identified in DSRI, GMI and TATA, while differences were more limited in AQI, SGI and DEPI. This finding indicates that manipulation is predominantly concentrated in selling/administrative expenses, receivables management and accruals.

Keywords*: *Earnings Manipulation, Earnings Management, Beneish M Score, Football Clubs, Union of European Football Associations.

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GENİŞLETİLMİŞ ÖZET

Çalışmanın Amacı

Bu çalışma, Avrupa futbol kulüplerinde kazanç manipülasyonu riskini uluslararası karşılaştırmalı bir perspektiften incelemeyi amaçlamaktadır. UEFA'ya bağlı 9 ulusal ligden borsada işlem gören 18 futbol kulübünün 2018-2024 yılları arasındaki finansal verileri, Beneish M-Score modeli kullanılarak analiz edilmiştir. Araştırma, toplam 126 kulüp-yıl gözlemi üzerinden M-Skorlarını ve sekiz farklı finansal değişkeni (DSRI, GMI, AQI, SGI, DEPI, SGAI, LVGI, TATA) değerlendirerek manipülasyon riskini ölçmeyi hedeflemektedir. Analizlerde özellikle, manipülasyonun yoğunlaştığı alanlar (satış/idari giderler, alacak yönetimi, tahakkuklar) belirlenerek, futbol endüstrisindeki finansal şeffaflık sorunlarına ışık tutmak amaçlanmıştır.

Araştırma Soruları

Araştırma, dört temel soruya yanıt vermeyi hedeflemektedir. Buna göre 1 - Avrupa futbol kulüplerinde kazanç manipülasyonu riski ne ölçüdedir ve bu risk zaman içinde (2018-2024) nasıl değişmektedir? 2 - Beneish M-Score modelinin finansal değişkenleri arasında manipülasyona en yatkın olanlar hangileridir? 3 - Manipülatör ve manipülatör olmayan kulüpler arasında değişkenlerde istatistiksel farklar var mıdır ve bu farklar hangi finansal alanlarda yoğunlaşmaktadır? Son olarak, futbol endüstrisine özgün dinamikleri (yüksek operasyonel maliyetler, değişken gelirler, Financial Fair Play (FFP) baskısı) manipülasyon eğilimini nasıl etkilemektedir?

Literatür Araştırması

Literatür, Beneish M-Score modelinin kazanç manipülasyonunu tespit etmedeki etkinliğini çeşitli sektörlerde doğrulamaktadır. Örneğin Beneish (1999), sekiz değişkenli modeli ile SEC tarafından cezalandırılan 74 firma üzerinden %76 doğruluk oranı elde etmiştir. Diğer sektörlerde, Tarjo & Herawati (2015) brüt kar marjı ve gider endekslerinin önemini vurgulamış; Kamal & Ahmad (2016) Malezya'da %82 doğruluk bulmuştur. Avrupa'da Repousis (2016) Yunanistan'da %33 manipülasyon oranı rapor ederken, Holda (2020) Varşova Borsası'nda %100 başarı göstermiştir. Türkiye'de Fındık & Öztürk (2016) BIST'te %50 risk tespit etmiş; Can & Özarı (2023) Beneish ile Benford Yasası'nı karşılaştırmıştır. Ancak futbol ile ilgili literatür oldukça sınırlıdır. Bu çalışma, futbol odaklı uluslararası karşılaştırma yaparak söz konusu boşluğu doldurmayı amaçlamaktadır.

Yöntem

Bu çalışma, UEFA'ya bağlı 9 ligden borsada işlem gören 18 futbol kulübün 2018 - 2024 finansal verilerini kapsar; toplam 126 kulüp/yıl gözlemi yapılmıştır. Veriler, KAP, Investing, Yahoo Finance ve WSJ gibi çeşitli kaynaklardan temin edilmiş; IFRS standartlarına göre hazırlanmış bilanço, gelir tablosu ve nakit akış tablolarından elde edilen veriler analizlerde kullanılmıştır. Analiz, Beneish (1999) sekiz değişkenli M-Score modeli ile gerçekleştirilmiştir. Elde edilen sonuçlar manipülatör/manipülatör olmayan gruplar arası farklar tanımlayıcı istatistiklerle değerlendirilmiştir. Yöntem pratiğinde modelin objektifliği korunurken, analizler futbolun volatil yapısına uyarlanmıştır.

Sonuç ve Değerlendirme

Sonuçlar 126 gözlemin %42'sinde manipülasyon riski gösterirken, en yüksek risk 2018'de (11 kulüp) gözlenmiştir; Fenerbahçe ve Ajax gibi kulüplerde ise 5 yıla varan uzun vadeli risk saptanmıştır. SGAI (68 vaka) en manipüle edilen değişkenken, GMI (17 vaka) en az etkilenmiştir; DSRI ve TATA'da manipülatör/manipülatör olmayan arası farklar oldukça belirgindir. Tanımlayıcı istatistikler, DSRI (ort. 1.196), SGAI (ort. 1.418) ve TATA'nın (pozitif manipülasyon ortalaması) riskli olduğunu doğrulamaktadır. Tartışmada, SGAI manipülasyonu operasyonel maliyet baskısına (maaşlar, transferler), DSRI ise erken gelir tanıma pratiğine bağlanmıştır; GMI'nin düşük manipülasyonun ise gelir volatilitesinden kaynaklandığı söylenebilir.

1. INTRODUCTION

In recent years, football has gone beyond being just a sport and has become a huge economic ecosystem on a global scale. According to Deloitte's (2024) annual report, the total revenue of the European football market is estimated to exceed EUR 30 billion in the 2022-2023 season and this figure is estimated to reach EUR 39.1 billion in the 2024-2025 season. These figures clearly demonstrate the financial size and economic impact of the football industry. While clubs are the cornerstones of this gigantic economic structure, sources of income include broadcasting rights, sponsorship agreements, ticket sales and player transfers. This huge financial volume has turned football clubs into structures where complex financial operations are carried out. However, an economy of this magnitude also brings along financial transparency and accountability issues. Financial manipulation and earnings manipulation emerge as a common risk in the financial statements of football clubs, posing serious threats to both the sustainability of the clubs and the trust of stakeholders.

Financial manipulation can be defined as fraudulent transactions carried out in order to present misleading information in the financial statements of companies in order to reflect their financial position more favourably or unfavourably than it actually is. Such manipulations may lead to misleading investors, distortion of market valuations and ultimately economic crises. Detection of financial manipulation, which is critical for the efficiency and transparency of financial markets, assumes an important function for both investors and regulators (Dechow, Ge & Schrand, 2010; p.345-346). Earnings manipulation, as a type of financial manipulation, refers to misleading arrangements that take advantage of the flexibility of accounting standards to make financial performance look better or worse than it actually is (Healy & Wahlen, 1999; p. 368). Such manipulations are usually carried out through methods such as misclassification of income and expenses, period shifts or changes in accounting estimates. The objectives include artificially increasing enterprise value, reducing borrowing costs or achieving certain performance targets. Although it may appear to be in compliance with accounting standards, such practices violate the primary purpose of financial reports and may mislead the decisions of users of financial information (Dechow & Skinner, 2000; p.236; Schipper, 1989; p.92).

Financial manipulation in football clubs is usually carried out through methods such as inflating revenues, hiding expenses or misrepresenting asset values. For example, fictitious revenue reporting in sponsorship deals, exaggeration of transfer fees or off-balance sheet debt are common forms of earnings manipulation (Pinnuck & Potter, 2006; p.501). Such manipulations are strategies that are frequently used by clubs in an effort to make their financial health look better than it actually is. Especially with the introduction of regulatory mechanisms such as Financial Fair Play (FFP) rules, it is thought that the tendency of clubs to resort to such manipulative practices has increased. In addition, it is accepted that the motivations of football clubs such as attracting investors are also effective in this (Peeters & Szymanski, 2014; p.345). Detection of earnings manipulation is critical for maintaining the transparency and credibility of the football industry. If the manipulation is overlooked, it may lead to asymmetric information problems among stakeholders, undermining the trust of both investors and fans in the clubs. Moreover, widespread manipulation may create unfair advantages by distorting the competitive balance in the sector (Andreff, 2007; p.653). In this context, analytical measures and models developed for the detection of earnings manipulation can increase the transparency of football clubs.

One of the prominent models for detecting earnings manipulation is the Beneish M Score developed by Messod D. Beneish. This model, which was first introduced in 1997 with five variables, was expanded to eight variables in 1999 and used to assess the risk of manipulation in the financial statements of enterprises (Beneish, 1997; Beneish, 1999). The Beneish M Score analyses the earnings manipulation tendencies of enterprises with a scoring system consisting of a combination of eight different financial ratios. This model aims to determine whether there is a manipulative intervention in the performance of the business by examining certain measures in the financial data. Beneish (1999) stated that the model was specifically designed to measure the risks of earnings manipulation of listed companies and revealed that this tool is an effective method that allows investors to recognise manipulation risks in advance. The advantages of the Beneish M-Score are that the model provides both an objective approach based on accounting data and a high accuracy rate in the early detection of manipulation. Especially considering the complex financial structures of football clubs and the increasing reporting obligations of listed clubs, the sectoral applicability of this model has a significant potential.

The purpose of this study is to comparatively evaluate the earnings manipulation risks of 18 football clubs in 9 national leagues affiliated to the Union of European Football Associations (UEFA) and whose shares are traded on stock exchanges in 2018-2024 by calculating the Beneish M-Score model. The study also analyses the manipulation risk in the financial variables in the model. In this context, the research consists of six chapters. The second section summarises the previous research on the research topic under the title of literature review. In the third section, under the methodology heading, the data sources used in the research and the Beneish M-Score model, which is the analysis method applied, are explained. In the fourth section, the results obtained from the analyses are presented under the title of findings. In the fifth section of the study, the findings are discussed in terms of theory and football clubs, and the limitations of the applied model are explained. In the conclusion section, comments and suggestions are presented in line with the findings obtained from the research.

2. LITERATURE REVIEW

When the literature on the subject is examined, it is observed that the Beneish-M Score model is used to calculate the earnings manipulation risk of companies in different sectors and studies have been conducted to determine the effectiveness of the model. Beneish M-Score is a model created by Prof. Dr. Messod Beneish in 1997 and developed in 1999 in order to determine whether there is earnings manipulation in the financial statements of companies. Beneish (1997) developed the original M-Score model using a sample of 64 entities that violated Generally Accepted Accounting Principles (GAAP) between 1982 and 1992 and a control group of entities with exceptional financial performance. This model, which includes five variables, was initially designed to assess the likelihood of earnings manipulation, largely related to management discretionary accruals (discretionary accruals). Later, Beneish (1999) extended the model to an eight-variable version that can detect earnings manipulation in more detail and tested the model on 74 manipulative firms sanctioned by the US Securities and Exchange Commission. The main differences between the Beneish (1997) and Beneish (1999) models can be listed as the number of variables (5 versus 8), the samples analysed (64 firms with GAAP violations and 74 firms with earnings manipulation) and the control group selection criteria (firms with unusual financial performance and firms matched on sectoral basis). The eight-variable model developed by Beneish (1999) is widely accepted and used in the literature as the standard version of M-Score since it provides a more comprehensive analysis and is methodologically more refined.

When the literature on companies operating in sectors other than football is examined, it is found that the Beneish M-Score model is used to analyse the risk of earnings manipulation in different sectors and countries and various studies have been conducted to evaluate the effectiveness of the model. Tarjo & Herawati (2015) found that the model is effective in detecting financial manipulation and especially gross profit margin, depreciation, selling and administrative expenses and total accrual indices are significant variables in this detection process. Kamal & Ahmad (2016), in their study on publicly traded companies in Malaysia, found that the model detects earnings manipulation with 82% accuracy in firms accused of false financial reporting and misstatement. Similarly, Aghghaleh, Mohamed & Rahmat (2016) found that the model identified financial manipulation with an accuracy rate of 73.17% in Malaysia. Anh & Linh (2016) found that about half of non-financial companies in Vietnam are at risk of earnings manipulation. Sutainim, Mohammed & Kamaluddin (2021) reported that sales growth index, accruals/total assets index and trade receivables index create significant differences between manipulator companies and others in Malaysian companies. Khatun, Ghosh & Kabir (2022) stated that commercial banks in Bangladesh can be categorised as manipulators and non-manipulators with the Beneish model, and that banks especially resort to methods of overstating revenues, reducing costs and changing accruals. In European studies, Repousis (2016) found that one-third of non-financial businesses in Greece may be manipulators, while Holda (2020) found that the model detected manipulation with 100% accuracy in companies on the Warsaw Stock Exchange. In addition, MacCarthy (2017) showed that the Beneish M-Score model largely detected Enron's financial manipulation. Halilbegovic et al. (2020) found that the model was effective in detecting manipulation in SMEs in Bosnia and Herzegovina.

Studies conducted in Turkey also support the effectiveness of the model. For example, Fındık & Öztürk (2016) found that approximately half of the companies in the BIST Manufacturing Index are at risk of manipulation, while Erdem (2020) showed that the probability of manipulation of firms in the BIST-100 index according to the Beneish M-Score model is effective on critical issues in audit reports. In other studies conducted in Turkey, Toplu, Calayoğlu & Azaltun (2021) found that the majority of companies traded on the BIST have different levels of financial manipulation risk, while Benligiray & Onay (2021) showed that the original and updated versions of the Beneish model give different results in detecting manipulation. Fidan (2021) found that firms operating in the stone and soil sector in the BIST engaged in earnings manipulation, while the most frequently emphasised issue in independent audit reports was revenue recognition. Finally, Can & Özarı (2023) compared the Beneish M-Score model and Benford's law by analysing the data of a bankrupt firm in BIST and found that both methods yield similar results in detecting manipulation. These findings in the literature reveal that the Beneish M-Score model is widely used in different sectors and countries for the detection of financial manipulation and its effectiveness is widely accepted.

When the literature on football clubs is analysed, it is noteworthy that there is a very limited number of studies in which the risk of earnings manipulation is measured by directly applying the Beneish M Score model. It has been observed that the studies are generally aimed at determining the levels of financial transparency, financial discipline and earnings management and earnings manipulation in the context of the compliance processes of football clubs with financial fair play rules. Dimitropoulos (2009) analysed the financial reporting processes of football clubs in Greece and found that clubs manipulate their financial statements to hide their debt burden and overstate their revenues. However, in this study, a specific model such as the Beneish M Score was not used, rather general accounting ratios and statistical analyses were preferred. Dimitropoulos (2011) analysed the effect of corporate governance quality on earnings management in football clubs in the European Union. In this context, data of 67 football clubs from 10 EU countries between 2006-2009 were used as a sample. In the analysis process, the impact of corporate governance factors was analysed by applying methods such as small positive income reporting (logit regression), performance-matched discretionary accruals (Jones model) and income smoothing (Spearman correlation) to evaluate earnings management. The results show that high board independence, managerial and institutional ownership, and small board size reduce aggressive earnings manipulation (income smoothing, accrual manipulation, and small positive income reporting) while improving financial reporting quality and that effective corporate governance mechanisms in football clubs are important in terms of protecting financial transparency and shareholder interests. Brooks (2012) examined the impact of UEFA's Financial Fair Play (FFP) regulations on earnings manipulation behaviours, player salaries, corporate governance and audit quality in European football clubs. In this context, the sample consists of 288 club-year observations collected from 48 top-level football clubs from 8 European Union countries (France, Germany, Greece, Italy, Netherlands, Portugal, Spain and United Kingdom) between 2006 and 2012. In the analysis, earnings manipulation is measured using the Jones model and OLS and logit regression analyses. The results show that clubs with high payrolls and clubs trying to comply with FFP regulations engage in more earnings manipulation, but strong corporate governance and high audit quality reduce these aggressive manipulation behaviours.

Drut & Raballand (2012) examined the financial management practices of football clubs and found that some clubs tend to maintain their position in the league by manipulating their revenues. The study argued that manipulation mostly takes place in the form of hiding transfer expenditures or exaggerating sponsorship revenues. However, again, the Beneish M Score is not used. Morrow (2013) discussed the financial sustainability problems of European football clubs and the effects of FFP. The study suggested that some clubs inflate their revenues or hide their expenses in order to comply with FFP rules, but did not present a model on how to detect these manipulations in a systematic way. Leach & Szymanski (2015) examined the financial vulnerabilities and manipulation tendencies of European football clubs and argued that clubs may resort to creative accounting techniques to hide their debt structures. The study emphasised the lack of transparency in the financial reporting processes of Italian and Spanish clubs in particular, but did not include the application of a model such as the Beneish M Score. While this situation provides strong clues to the existence of manipulation, it reveals the lack of a systematic detection method. Dimitropoulos, Leventis & Dedoulis (2016) examine the impact of UEFA's Financial Fair Play (FFP) Regulation on the governance policies and accounting quality of European football clubs. The study uses a sample of football clubs from 15 European countries between 2008 and 2014. As a methodology, three common proxy variables such as earnings management (Jones model and revenue smoothing), contingent accounting conservatism (Ball and Shivakumar model) and auditor change are analysed to assess accounting quality, and their changes in the post FFP period are tested with GLS random effects regression. The findings show that with the implementation of FFP, club managers implemented aggressive earnings management, switched from large audit firms (big-4) to local auditors and were less conservative in timely loss recognition, suggesting that accounting quality deteriorated and clubs tried to create an image of financial soundness to secure licences and funding from UEFA. Özevin (2017) examined the impact of FFP rules on the five major leagues in Europe and Turkish Super League clubs and argued that these regulations increased financial transparency. Neri et al (2021) examined whether Italian Serie A clubs engaged in earnings manipulation through player transfers after the implementation of Financial Fair Play (FFP) rules. With a sample of 275 club-year observations from 38 clubs between 2005 and 2018, the analysis using the fixed effects OLS method based on Bartov's asset sales model revealed that net capital gains from player sales are positively related to club profitability and that the indebtedness ratio has become associated with manipulation after FFP, especially in leading clubs.

Apart from the studies summarised above, there is a study in the literature on football clubs that measures the risk of earnings manipulation in football clubs according to the Beneish M-Score model. Kokic, Gligoric & Knezevic (2018) examined whether Serbian Super League football clubs manipulate earnings in their financial statements using the Beneish M-score model. In this context, the financial statements of 13 football clubs in the Serbian Super League between 2009-2016 were analysed. As a result of the study, it was determined that 4 of the 13 clubs in the sample (approximately 31%) exceeded the M-score threshold of -2.22 and that these clubs manipulated their financial statements. To the best of the authors' knowledge, no other study directly applies the Beneish M-Score model to publicly traded football clubs. Therefore, it is thought that this study will contribute to the literature in the context of comparative analysis of earnings manipulation in football clubs according to the Beneish M Score model over 18 football clubs in 9 national leagues affiliated to UEFA.

3. METHODOLOGY

3.1. Data

In this study, the data of a total of 18 football clubs in 9 different national leagues affiliated to UEFA, which are traded on stock exchanges and whose financial information is fully accessible due to the availability of financial data, for the financial periods between 2018-2024, covering the period from 1 June to 31 May, are examined. The financial data used in the analysis were obtained from annual statement of financial position (balance sheets), comprehensive income Statement and cash flow statements prepared in accordance with International Financial Reporting Standards. Assuming that football leagues usually end on 31 May and preparations for the new season start on 1 June, the financial reporting periods of the clubs are defined as 1 June-31 May. Since the financial statements of the clubs included in the analysis were not available or incomplete for the periods before 2017, the years 2018-2024 were selected as the period of analysis for which complete and reliable data were available. Financial information of football clubs in Turkey is obtained from the official website (www.kap.org.tr) of the Public Disclosure Platform. Data on other clubs were collected from reliable secondary sources such as Investing (https://tr.investing.com/equities/europe), Yahoo Finance (www.finance.yahoo.com) and The Wall Street Journal (www.wsj.com). The football clubs included in the study are listed in Table 1, taking into account the countries and leagues they are affiliated with.

Table 1. Football Clubs in the Scope of Analysis

No	Country/League	Club Name
1	**Türkiye / Spor Toto Super League**	Beşiktaş Futbol Yatırımları Sanayi ve Ticaret A.Ş
2		Fenerbahçe Futbol A.Ş.
3		Galatasaray Sportif Sınai ve Ticari Yatırımlar A.Ş.
4		Trabzonspor Sportif Yat. ve Futbol İşl. Tic. A.Ş.
5	**Italy / Serie A**	Juventus Football Club S.p.A.
6		Societa Sportiva Lazio S.p.A.
7	**England / Premier League**	Manchester United Plc
8	**Scotland / Scottish Premiership**	Celtic PLC
9	**France / Ligue 1**	Olympique Lyonnais (Eagle Football Group SA)
10	**Netherlands /Eredivisie**	AFC Ajax
11	**Denmark / Superliga**	Aalborg Boldspilklub AS
12		Aarhus Elite
13		Broendbyernes IF Fodbold AS
14	**Germany / Bundesliga**	Borussia Dortmund GmbH & Co

15	**Portugal / Liga NOS**	Futebol Clube do Porto SAD
16		Sport Lisboa e Benfica-Futebol SAD
17		Sporting Clube de Portugal Futebol SAD
18		Sporting Clube de Braga-Futebol SAD

3.2. Method of Analysis

In the analysis process, the earnings manipulation risks of a total of 18 football clubs in 9 national leagues affiliated to UEFA for the years 2018-2024 were calculated by applying the Beneish M score model on the data obtained from annual balance sheets, detailed income statements and cash flow statements. The calculated Beneish M scores and the results of the eight variables in the model used to calculate the score are interpreted separately. During the analysis process, 126 football club-year observations were made.

The Beneish M-Score model was introduced by Prof. Dr. Messod Beneish in 1997 to identify earnings manipulation in financial statements. This model assesses the possibility of manipulation of companies through financial ratios and various indicators. Beneish (1997) designed the first M-Score model using a data set of 64 companies that violated GAAP rules and a control group of companies that exhibited remarkable financial success between 1982 and 1992. This initial model included five basic indices: Days Sales in Receivables Index (DSRI), Gross Margin Index (GMI), Asset Quality Index (AQI), Sales Growth Index (SGI) and Total Accruals to Total Assets (TATA). Later, Beneish (1999) extended the 1997 model with eight variables (Depreciation Index (DEPI), Sales, General, and Administrative Expenses Index (SGAI) and Leverage Index (LVGI) were added to the above five variables) and presented a model to detect earnings manipulation in more detail. The updated model is based on a sample of 74 companies that were found to have manipulated earnings between 1982 and 1992 and were subject to criminal proceedings by the United States Securities and Exchange Commission (SEC). The main differences between Beneish's 1997 and 1999 models can be summarised as the increase in the number of variables (from 5 to 8), the sample groups analysed (64 GAAP violators versus 74 earnings manipulators) and the comparison groups (firms with exceptional financial performance versus firms with sectoral compliance). The Beneish (1999) model stands out as the most widely accepted form of M-Score in the literature and is preferred more frequently in practice due to its detailed structure and methodological superiority. In this study, the eight-variable Beneish (1999) model is taken as a basis. According to the criteria of the model, companies with an M-Score value higher than -2.22 have a high risk of earnings manipulation, while those below this value are classified as low risk (Khatun, Ghosh & Kabir, 2022; p.306; MacCarthy, 2017; p.161). The relevant model is explained in detail below (Beneish, 1999; p.27);

$$\text{Beneish M-Score} = -4.84 + (0.92 \times DSRI) + (0.528 \times GMI) + (0.404 \times AQI) + (0.892 \times SGI) + (0.115 \times DEPI) - (0.172 \times SGAI) - (0.327 \times LVGI) + (4.679 \times TATA)$$

Variables in the model;

- Days Sales in Receivables Index (DSRI): This index is calculated by comparing the ratio of trade receivables to sales in the current year (t) with the ratio in the previous year (t-1) to assess whether receivables and revenues have been in line for two years. If the DSRI is greater than 1, this indicates that receivables are increasing faster than sales, which may suggest the possibility of premature recognition of revenues, a deterioration in the company's financial position, or the use of aggressive accounting methods. In addition, it may indicate that the firm offers more flexible credit facilities to customers to encourage sales (Aghghaleh, Mohamed & Rahmat, 2016; p.60). On the other hand, a DSRI value below 1 indicates that receivables are decreasing relative to sales. In the model, if the DSRI value is above 1.465, it is assumed that the relevant financial elements are manipulated or there are changes in credit policies (MacCarthy, 2017; p.162). The index is calculated by the following formula (Beneish, 1999; p.26);

(Trade Receivables$_t$ / Sales$_t$) / (Trade Receivables$_{t-1}$ / Sales$_{t-1}$)

- Gross Margin Index (GMI): This index is a value that compares the gross profit margin of an enterprise in a given year (t) with the gross profit margin of the previous year (t-1). The GMI is used to analyse changes in the profitability of an enterprise. If GMI is greater than 1, this indicates that the gross profit margin of the enterprise has declined compared to the previous year and that the enterprise has difficulties in maintaining its profitability. This can often be attributed to an entity's inability to manage its costs effectively or losing pricing advantage in the market. Conversely, a GMI value significantly less than 1 indicates a significant increase in gross margin. Although this may initially be perceived as a positive development, it may raise suspicion that the entity may have manipulated its financial results to overstate them. Businesses with either an extreme decline or a sudden increase in gross margin may tend to distort their earnings. Therefore, GMI is included in the Beneish model as an important tool to detect possible fraud in financial data. In the model, a GMI value above 1.193 is considered as a sign that an entity manipulates its gross profit (Harrington, 2005;p.12). GMI is calculated as follows (Holda, 2020; p.394);

(Sales$_{t-1}$ – Cost of Sales$_{t-1}$ / Cost of Sales$_{t-1}$) / (Sales$_t$ – Cost of Sales$_t$ / Cost of Sales$_t$).

- Asset Quality Index (AQI): This index is a measurement obtained by dividing the share of an enterprise's intangible assets in total assets in the current year (t) by the same ratio of the previous year (t-1). This index is an indicator that evaluates the ratio of assets that can provide economic benefits in the future within the total assets of the enterprise (Aghghaleh, Mohamed & Rahmat, 2016; p.60). An increase in the AQI may indicate that the weight of non-current items, such as goodwill, intangible assets or other items of uncertain long-term value, in total assets has increased compared to the previous year. This may indicate an increased likelihood of earnings manipulation. In addition, a high AQI value may give a clue that expenses may have been recognised as assets in the balance sheet and their effects deferred instead of being recognised in the income statement (Warshavsky, 2012;p.17). According to the Beneish model, an AQI exceeding 1,254 is considered to be an indicator that the business distorts gross profit figures (MacCarthy, 2017; p.162). AQI is calculated by the following formula (Beneish, 1999; p:27);

[1 – (Current Assets$_t$ + Tangible Fixed Assets$_t$ / Total Assets$_t$)] / [1 – (Current Assets$_{t-1}$ + Tangible Fixed Assets$_{t-1}$ / Total Assets$_{t-1}$)]

- Sales Growth Index (SGI): SGI is a measure that evaluates the annual change in sales by calculating the ratio of an enterprise's sales in the current year (t) compared to sales in the previous year (t-1). A SGI higher than 1 indicates that sales have increased compared to the previous year. Although an increase in sales is generally seen as a positive development by investors, companies with excessive growth may distort their financial results, especially if the growth is likely to become unsustainable. This may be due to pressure from executives to meet earnings expectations or fear of severe declines in share values if the pace of growth slows. Therefore, if high sales growth, in combination with other indicators in the model, presents negative signs, this may be a warning that the risk of manipulation of financial data has increased. According to the Beneish M score model, an SGI exceeding 1,607 is a strong indicator of the possibility of manipulation in sales figures (MacCarthy, 2017; p.162). SGI is calculated by the following formula (Beneish, 1999; p:27);

Sales$_t$ / Sales$_{t-1}$

- Depreciation Index (DEPI): DEPI is an indicator that allows analysing the depreciation allocation rate of an enterprise by comparing the current year (t) with the previous year (t-1) (Holda, 2020; p.395). If the DEPI value is higher than 1, it indicates that the depreciation rate has decreased compared to the previous year and is considered as a sign that the entity has either revised its assets to extend their useful life or implemented a depreciation policy that increases revenue. Such adjustments may delay the recognition of expenses and artificially increase the income presented in the financial statements (Anh & Linh, 2016; p.18). According to the Beneish M-Score Model, a DEPI above 1.077 indicates the possibility of manipulation in asset valuations or economic life estimates (MacCarthy, 2017; p.162). DEPI is calculated by the following formula (Beneish, 1999; p.27);

(Depreciation$_{t-1}$ / (Depreciation$_{t-1}$ + Tangible Fixed Assets$_{t-1}$)) / (Depreciation$_t$ / (Depreciation$_t$ + Tangible Fixed Assets$_t$))

- Sales, General, and Administrative Expenses Index (SGAI): This index is a measure used to examine the change in the ratio of sales, general, and administrative expenses to sales revenues between the current year (t) and the previous year (t-1) (MacCarthy, 2017; p.162). A SGAI higher than 1 indicates that sales, general, and administrative expenses have increased in the current period compared to sales compared to the previous year. This may increase the possibility of financial manipulation, such as inflating sales figures or covering up poor operational performance. In addition, an increase in these expenses without significant growth in sales may indicate that executives are overpaid or that there is a loss of efficiency in marketing and management processes, which may trigger the risk of earnings manipulation (Anh & Linh, 2016; p.18). According to the Beneish M-Score Model, an SGAI exceeding 1.041 indicates a high risk of manipulation in these expense items (MacCarthy, 2017; p.162). SGAI is calculated by the following formula (Beneish, 1999; p.27);

(Sales, General, and Administrative Expenses_t / Sales_t) / (Sales, General, and Administrative Expenses_{t-1} / Sales_{t-1})

- Leverage Index (LVGI): This index is an indicator that analyses the change in a company's use of external resources by comparing the ratio of total debt to total assets in the current year (t) with the same ratio in the previous year (t-1) (Anh & Linh, 2016; p.19). When LVGI is higher than 1, it means that the company's indebtedness level has increased and its financial liabilities have become heavier. This increase in the amount of debt may lead the company to become more prone to distort its financial data for reasons such as the effort to exceed debt limits or the need to maintain access to capital resources (Holda, 2020; p.395). However, a decrease in LVGI should not be ignored, as this may indicate that the company has excessively increased its equity capital through stock sales while paying down its debts, which can be considered as a signal of fraudulent activities. According to the Beneish M-Score Model, a LVGI exceeding 1.111 indicates a high risk of manipulation in the leverage structure (MacCarthy, 2017; p.162). LVGI is calculated by the following formula (Beneish, 1999; p.27);

(Total Liabilities and Debt_t / Total Assets_t) / (Total Liabilities and Debt_{t-1} / Total Assets_{t-1})

- Total Accruals to Total Assets (TATA): This index is a measure used to assess the level of cash conversion of a company's accounting earnings and is calculated by the following formula (Beneish, 1999; p.27);

(Net Profit_t – Cash Flow from Operating Activities_t) / Total Assets_t

Accruals reflect the difference between the profit or loss calculated using the company's accounting method and the cash-based profit or loss. This difference is standardised by dividing it by total assets to enable comparisons between companies of different sizes. Companies that report high accounting profits without cash flows, i.e. those that generate large accruals, may tend to manipulate their financial data. High accruals, especially in the positive direction (i.e. low cash inflows), indicate an increased likelihood of earnings distortion (Holda, 2020; p.396). According to the Beneish M score model, a TATA exceeding 0.031 indicates a high risk of manipulation (MacCarthy, 2017; p.163).

4. Findings

Within the scope of the research, calculations regarding the eight indices of football clubs for the years 2018-2024 were made in the Excel programme and Beneish M Scores were determined. The findings are presented annually in Table 2 for the 18 football clubs included in the analysis. In the table, the data evaluated according to the cut-off points of the model (presented in the rightmost column in the table) are highlighted in colours: Red indicates that an entity is at risk of earnings manipulation, either for the relevant index or in general, while green indicates that there is no such risk.

Table 2. Beneish M Scores of Football Clubs

Beşiktaş	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	1.130	0.538	2.180	0.513	1.199	0.563	0.486	> 1.465
GMI	131.560	-0.008	-4.530	-0.222	0.844	1.042	1.119	> 1.193
AQI	0.669	0.797	0.457	1.465	2.847	1.797	1.653	> 1.254
SGI	0.686	0.801	1.074	1.848	2.714	1.490	1.446	> 1.607
DEPI	0.918	0.703	1.052	0.745	1.292	0.753	0.802	> 1.077
SGAI	1.625	1.249	0.797	0.513	0.594	1.987	3.966	> 1.041
LVGI	1.113	1.122	0.927	1.134	0.486	1.702	1.502	> 1.111
TATA	-0.366	-0.422	-0.011	-0.330	-0.212	-0.451	-0.458	> 0.031
Beneish M Score	**64.294**	**-5.789**	**-4.457**	**-4.162**	**-0.825**	**-4.638**	**-5.070**	> -2.22

Fenerbahçe	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	2.509	0.653	1.301	0.816	1.087	0.802	0.802	> 1.465
GMI	0.792	0.996	0.622	-2.069	-0.273	1.469	1.469	> 1.193
AQI	0.793	1.362	1.019	0.751	2.952	1.735	1.667	> 1.254
SGI	1.192	0.769	1.265	1.892	3.178	1.553	1.334	> 1.607
DEPI	0.980	0.945	0.939	1.140	0.905	0.965	1.039	> 1.077
SGAI	1.163	0.993	0.705	0.945	1.176	0.938	0.938	> 1.041
LVGI	0.777	1.042	0.988	0.996	0.967	0.856	0.856	> 1.111
TATA	0.056	-0.187	0.052	-0.063	-0.090	-0.023	-0.021	> 0.031
Beneish M Score	**-0.808**	**-3.758**	**-1.867**	**-3.843**	**-0.790**	**-1.677**	**-1.882**	> -2.22

Galatasaray	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	1.417	0.571	1.454	0.497	1.690	0.699	0.947	> 1.465
GMI	-0.274	1.012	-0.283	33.489	0.036	-9.895	-10.032	> 1.193
AQI	1.000	1.112	0.972	1.057	0.992	0.934	0.930	> 1.254
SGI	1.478	0.970	0.688	1.923	2.872	2.503	2.328	> 1.607
DEPI	1.006	0.990	1.000	1.046	0.962	0.973	1.002	> 1.077
SGAI	0.828	1.238	1.428	0.791	1.568	0.710	0.699	> 1.041
LVGI	0.927	0.990	1.131	1.030	0.942	0.737	0.184	> 1.111
TATA	-0.114	-0.061	-0.146	-0.138	-0.368	-0.039	-0.039	> 0.031
Beneish M Score	**-2.820**	**-3.173**	**-3.830**	**14.444**	**-2.493**	**-7.245**	**-7.060**	> -2.22

Trabzonspor	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	0.679	2.060	0.604	1.161	0.687	0.592	0.922	> 1.465
GMI	-2.756	1.107	-1.010	0.654	0.490	1.044	1.044	> 1.193
AQI	1.035	0.803	0.388	0.869	1.383	0.918	0.681	> 1.254
SGI	1.897	1.081	0.919	1.828	3.284	0.882	0.821	> 1.607
DEPI	1.012	1.236	1.923	1.322	0.906	1.283	1.639	> 1.077
SGAI	0.666	1.176	1.304	0.747	1.305	1.471	1.375	> 1.041
LVGI	0.774	0.954	0.801	0.886	0.914	0.788	0.667	> 1.111
TATA	-0.424	0.114	-0.288	-0.278	0.149	-0.144	-0.144	> 0.031
Beneish M Score	**-5.798**	**-0.912**	**-5.454**	**-3.012**	**-0.184**	**-3.624**	**-3.374**	> -2.22

Juventus	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	1.062	0.985	1.355	0.785	0.896	0.586	0.682	> 1.465
GMI	5.313	-0.067	-0.121	1.042	0.993	0.949	1.009	> 1.193
AQI	1.196	1.078	0.920	0.957	0.983	0.950	0.877	> 1.254
SGI	1.046	1.154	1.222	0.830	0.926	1.144	0.882	> 1.607
DEPI	0.856	0.861	1.075	0.977	0.997	1.210	1.281	> 1.077
SGAI	2.459	1.019	2.811	1.368	1.098	0.796	0.947	> 1.041
LVGI	1.020	1.066	0.824	1.243	0.831	1.153	1.143	> 1.111
TATA	-0.032	-0.039	-0.026	-0.296	-0.222	-0.098	-0.226	> 0.031
Beneish M Score	**-0.449**	**-3.109**	**-2.948**	**-4.357**	**-3.654**	**-3.227**	**-3.984**	> -2.22

Lazio	2018	2019	2020	2021	2022	2023	2024	Manipulation Threshold
DSRI	1.371	0.755	1.277	0.572	1.105	0.967	1.077	> 1.465
GMI	1.472	-1.737	-0.055	1.059	1.111	1.007	0.944	> 1.193
AQI	0.914	1.192	0.902	1.004	1.017	0.946	0.885	> 1.254
SGI	1.241	0.971	0.910	1.591	0.788	1.117	1.489	> 1.607
DEPI	0.953	0.818	1.070	0.988	1.029	1.122	1.007	> 1.077
SGAI	2.154	4.488	2.327	0.952	0.917	1.003	0.796	> 1.041
LVGI	0.864	1.068	1.091	1.092	1.042	1.108	0.968	> 1.111
TATA	0.189	-0.049	-0.188	-0.296	0.037	-0.210	0.073	>0.031
Beneish M Score	**-0.984**	**-4.971**	**-4.029**	**-3.720**	**-2.332**	**-3.427**	**-1.662**	> -2.22

Manchester United	2018	2019	2020	2021	2022	2023	2024	Manipulation Threshold
DSRI	2.024	0.134	8.440	0.583	0.839	0.881	0.765	> 1.465
GMI	1.289	1.060	0.533	0.958	1.045	1.044	1.027	> 1.193
AQI	0.993	1.004	1.129	0.971	0.991	1.045	1.073	> 1.254
SGI	0.800	1.063	0.812	0.971	1.180	1.112	1.135	> 1.607
DEPI	0.939	1.039	1.030	0.991	0.887	0.966	0.916	> 1.077
SGAI	1.391	1.080	1.194	1.218	1.021	0.806	0.856	> 1.041
LVGI	1.046	0.997	1.033	1.050	1.150	1.022	0.990	> 1.111
TATA	-0.086	-0.151	-0.014	-0.163	-0.164	-0.094	-0.148	> 0.031
Beneish M Score	**-2.056**	**-3.902**	**3.896**	**-3.741**	**-3.279**	**-2.868**	**-3.206**	> -2.22
Celtic	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	1.545	1.457	1.263	0.929	1.135	0.839	0.751	> 1.465
GMI	1.106	-3.410	0.285	0.658	5.645	-0.194	-0.257	> 1.193
AQI	1.330	0.960	1.424	0.951	1.238	0.719	0.559	> 1.254
SGI	1.121	0.821	0.842	0.865	1.452	1.358	1.412	> 1.607
DEPI	0.888	0.857	0.827	1.020	0.905	1.034	1.188	> 1.077
SGAI	1.410	0.989	1.386	1.116	0.760	0.682	0.623	> 1.041
LVGI	1.080	0.835	1.016	1.121	1.188	0.878	0.763	> 1.111
TATA	0.019	0.009	0.025	-0.005	-0.026	-0.046	-0.021	> 0.031
Beneish M Score	**-1.701**	**-4.481**	**-2.558**	**-2.948**	**0.445**	**-3.171**	**-3.118**	> -2.22
Olympique Lyonnais	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	0.486	1.519	0.896	1.842	0.732	0.582	0.734	> 1.465
GMI	0.823	1.154	13.387	-0.146	-5.236	-0.670	0.548	> 1.193
AQI	1.830	1.014	1.360	0.841	0.926	0.731	0.950	> 1.254
SGI	1.460	0.763	0.818	0.654	1.358	1.241	1.646	> 1.607
DEPI	0.750	0.780	0.712	0.943	1.217	1.186	0.960	> 1.077
SGAI	0.770	1.359	1.293	1.360	0.899	1.056	0.809	> 1.041
LVGI	0.980	0.992	1.156	1.227	1.066	0.975	1.082	> 1.111
TATA	0.065	0.006	0.010	-0.130	0.000	0.021	0.088	> 0.031
Beneish M Score	**-1.982**	**-2.183**	**3.860**	**-3.435**	**-5.710**	**-3.524**	**-1.996**	> -2.22
AFC Ajax	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	1.401	0.563	1.053	1.374	0.730	1.363	1.985	> 1.465
GMI	1.023	0.977	1.010	1.051	0.986	0.998	1.003	> 1.193
AQI	2.889	0.925	1.536	1.019	0.866	1.305	1.190	> 1.254
SGI	0.786	2.146	0.814	0.771	1.512	1.038	0.803	> 1.607
DEPI	1.000	0.989	1.124	0.885	1.032	0.908	0.926	> 1.077
SGAI	2.504	0.669	0.949	1.329	0.802	0.981	1.196	> 1.041
LVGI	1.104	1.167	1.199	1.017	1.026	0.978	1.063	> 1.111
TATA	0.104	0.008	0.064	0.012	-0.060	0.105	0.001	> 0.031
Beneish M Score	**-1.331**	**-1.862**	**-2.117**	**-2.324**	**-2.587**	**-1.500**	**-1.728**	> -2.22
Aalborg	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	1.045	0.461	11.215	0.216	1.765	1.026	0.413	> 1.465
GMI	0.955	1.182	1.115	0.881	0.873	1.018	1.034	> 1.193
AQI	0.194	4.567	0.534	0.982	1.265	0.693	0.711	> 1.254
SGI	1.107	0.863	0.723	1.473	1.325	0.961	0.883	> 1.607
DEPI	0.721	0.285	0.836	0.889	0.921	0.874	0.729	> 1.077
SGAI	0.894	1.079	1.428	0.732	0.974	1.084	1.099	> 1.041
LVGI	1.180	1.769	1.040	1.031	1.219	1.049	0.963	> 1.111
TATA	-0.128	-0.208	-0.042	-0.142	0.205	-0.054	0.018	> 0.031

Beneish M Score	**-3.365**	**-2.880**	**6.242**	**-3.490**	**-0.561**	**-2.901**	**-3.174**	> -2.22
Aarhus Elite	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	1.128	1.500	1.597	0.980	0.475	1.258	2.960	> 1.465
GMI	0.917	0.997	0.978	1.083	0.990	0.923	0.979	> 1.193
AQI	0.728	0.645	1.170	1.696	1.469	0.992	1.181	> 1.254
SGI	1.016	1.155	0.934	1.178	1.313	0.943	0.983	> 1.607
DEPI	0.967	0.886	0.987	0.863	0.813	0.767	1.073	> 1.077
SGAI	1.052	0.868	1.199	0.998	0.852	1.084	1.230	> 1.041
LVGI	1.000	0.769	1.161	0.886	0.951	0.515	0.568	> 1.111
TATA	-0.185	-0.018	-0.038	0.132	-0.214	0.153	0.205	> 0.031
Beneish M Score	**-3.379**	**-2.026**	**-2.199**	**-1.373**	**-3.482**	**-1.505**	**0.441**	> -2.22
Broendbyernes IF	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	1.933	0.442	4.370	0.722	0.552	1.158	1.737	> 1.465
GMI	1.095	1.022	1.077	0.748	1.388	0.874	0.963	> 1.193
AQI	0.917	0.688	0.661	0.944	2.169	0.987	0.987	> 1.254
SGI	1.263	0.943	0.647	2.560	0.762	1.544	1.029	> 1.607
DEPI	0.982	1.034	1.131	0.959	0.800	2.457	0.772	> 1.077
SGAI	1.286	0.704	1.368	0.477	1.396	1.194	1.194	> 1.041
LVGI	1.458	1.643	0.510	0.803	1.140	0.614	1.771	> 1.111
TATA	0.035	-0.226	-0.115	0.094	-0.035	-0.043	-0.028	> 0.031
Beneish M Score	**-1.406**	**-4.371**	**-0.219**	**-0.912**	**-2.728**	**-1.860**	**-2.245**	> -2.22
Borussia Dortmund	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	0.357	1.432	1.725	1.046	1.144	0.681	1.200	> 1.465
GMI	0.973	1.006	1.012	1.002	0.998	0.994	0.999	> 1.193
AQI	0.989	1.068	1.278	0.955	0.902	1.222	1.129	> 1.254
SGI	1.321	0.913	0.838	0.852	1.186	1.184	1.464	> 1.607
DEPI	0.725	1.054	0.966	0.944	0.994	1.023	1.144	> 1.077
SGAI	0.794	1.203	1.408	1.097	0.908	0.858	0.791	> 1.041
LVGI	0.842	0.992	1.413	1.179	0.836	1.108	1.102	> 1.111
TATA	-0.286	-0.254	-0.084	-0.197	-0.146	-0.088	-0.005	> 0.031
Beneish M Score	**-4.085**	**-3.345**	**-2.442**	**-3.590**	**-2.836**	**-2.941**	**-1.834**	> -2.22
Porto	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	1.653	0.812	0.952	1.056	0.956	0.632	0.308	> 1.465
GMI	1.005	0.986	1.015	0.987	1.013	0.999	1.000	> 1.193
AQI	0.723	0.948	1.080	1.279	1.045	0.698	0.748	> 1.254
SGI	1.066	1.598	0.499	1.750	0.947	1.155	1.214	> 1.607
DEPI	0.956	1.200	0.125	1.271	0.938	0.930	1.534	> 1.077
SGAI	1.116	0.503	2.748	0.625	29.681	0.985	0.916	> 1.041
LVGI	1.053	0.928	1.179	1.037	0.772	1.240	1.050	> 1.111
TATA	0.003	0.009	-0.241	0.132	0.090	-0.001	-0.095	> 0.031
Beneish M Score	**-1.958**	**-1.972**	**-4.517**	**-0.951**	**-6.986**	**-2.892**	**-3.412**	> -2.22
Benfica	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	1.212	0.738	1.136	0.806	1.048	0.993	0.730	> 1.465
GMI	1.237	107.744	-0.021	-0.263	-3.882	0.567	0.812	> 1.193
AQI	0.764	0.230	5.661	1.027	0.976	0.989	1.124	> 1.254
SGI	0.948	1.363	0.845	0.672	1.801	1.156	1.057	> 1.607
DEPI	1.371	1.002	0.707	0.853	0.995	1.107	0.994	> 1.077
SGAI	1.897	1.072	0.384	0.655	1.065	1.090	1.367	> 1.041
LVGI	0.947	0.935	0.571	1.092	1.237	0.995	1.116	> 1.111
TATA	0.075	0.105	0.210	0.137	0.013	0.107	0.096	> 0.031
Beneish M Score	**-2.046**	**54.152**	**0.046**	**-2.955**	**-4.338**	**-2.082**	**-2.378**	> -2.22
Sporting Clube Portugal	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	0.280	1.356	1.421	0.873	0.697	1.011	1.839	> 1.465
GMI	0.754	1.317	2.901	0.629	-1.663	1.682	-0.930	> 1.193
AQI	1.292	0.950	0.895	1.061	0.991	0.966	0.906	> 1.254
SGI	1.059	1.149	0.897	0.860	2.098	1.025	0.831	> 1.607
DEPI	1.000	1.035	1.005	0.986	0.991	0.904	0.991	> 1.077
SGAI	1.599	0.831	0.644	0.664	1.270	1.218	1.827	> 1.041
LVGI	1.100	0.986	0.855	1.093	0.872	0.722	0.640	> 1.111
TATA	-0.034	0.067	0.248	-0.109	0.272	0.235	0.301	> 0.031

Beneish M Score	**-3.396**	**-1.521**	**0.045**	**-3.379**	**-1.921**	**-0.957**	**-1.533**	> -2.22
Sporting Clube de Braga	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Manipulation Threshold**
DSRI	0.462	1.852	0.838	0.505	1.132	0.666	1.354	> 1.465
GMI	-121.461	-0.117	-0.393	-1.276	1.844	-2.082	-0.397	> 1.193
AQI	1.546	0.877	0.944	1.048	0.857	1.119	1.024	> 1.254
SGI	1.165	1.180	0.981	1.131	1.051	1.118	1.315	> 1.607
DEPI	0.836	0.889	1.087	1.443	1.514	1.220	1.114	> 1.077
SGAI	3.840	0.848	1.109	1.195	0.872	1.341	1.572	> 1.041
LVGI	1.115	0.946	0.800	0.993	0.923	0.878	0.974	> 1.111
TATA	0.244	0.283	0.238	0.126	0.208	0.356	0.167	> 0.031
Beneish M Score	**-66.671**	**-0.822**	**-2.234**	**-3.391**	**-0.847**	**-2.586**	**-1.897**	> -2.22

When Table 2 is analysed, it can be said that football clubs are at risk of earnings manipulation at least once and at most five times during the analysis period in terms of Beneish M scores. Fenerbahçe, AFC Ajax, Aarhus Elite and Sporting Clube Portugal were found to be the football clubs with the highest earnings manipulation risk in the analysis period and their Beneish M scores were greater than -2.22 in five years of the seven-year analysis period. Benfica, Olympique Lyonnais and Broendbyernes IF in four years, Porto and Sporting Clube de Braga in three years, Aalborg, Manchester United, Celtic, Lazio, Trabzonspor and Beşiktaş in two years and Galatasaray, Juventus, Borussia Dortmund in one year of the seven-year analysis period.

Table 3 presents the number of manipulator (M) and non-manipulator (NM) football clubs in terms of the eight variables in the model and the cut-off points of Beneish M scores.

Table 3. Number of Manipulator and Non-Manipulator Football Clubs in Variable Context

VARIABLES	**2018**		**2019**		**2020**		**2021**		**2022**		**2023**		**2024**		**Total**	
	M	**NM**	**M**	**NM**	**M**	**NM**	**M**	**NM**	**M**	**NM**	**M**	**NM**	**M**	**NM**	**M**	**NM**
DSRI	5	13	4	14	6	12	1	17	2	16	0	18	4	14	22	104
GMI	5	13	3	15	2	16	1	17	3	15	2	16	1	17	17	109
AQI	5	13	2	16	5	13	3	15	6	12	3	15	2	16	26	100
SGI	1	17	1	17	0	18	6	12	6	12	2	16	3	15	19	107
DEPI	1	17	2	16	4	14	4	14	3	15	7	11	6	12	27	99
SGAI	13	5	9	9	13	5	7	11	8	10	9	9	9	9	68	58
LVGI	4	14	4	14	6	12	5	13	5	13	3	15	4	14	30	96
TATA	7	11	4	14	5	13	5	13	6	12	5	13	6	12	38	88
Beneish M Score	**11**	**7**	**8**	**10**	**9**	**9**	**4**	**14**	**7**	**11**	**6**	**12**	**8**	**10**	**53**	**73**

In the study, 126 (18x7) football club-year observations were conducted in the context of 18 football clubs and a 7-year analysis period. In terms of the Beneish M score, 53 (approximately 42%) of the 126 football club observations were found to be at the risk of earnings manipulation during the analysis period, while 73 (approximately 58%) were not at the risk of earnings manipulation. According to this finding, it is possible to say that the number of football clubs at risk of earnings manipulation in the analysis period is lower than the number of clubs that are not at risk of earnings manipulation. However, it was also determined that the year with the highest risk of earnings manipulation in the analysis period in terms of Beneish M score was 2018 with 11 football clubs, while the year with the lowest risk was 2021 with 4 football clubs. When the eight variables in the Beneish M score model are analysed, it is determined that the most manipulated variables in the analysis period are SGAI with 68 observations. On the other hand, it was determined that the least manipulated variable was GMI with 17 observations.

Table 4 presents the descriptive statistics of the Beneish M Score model for the whole sample of 18 football clubs and the subgroups (Manipulator Group and Non-Manipulator Group) disaggregated by manipulation risk between 2018 and 2024. The mean Beneish M Score for the whole sample is calculated as -1.949, which is greater than the manipulation risk threshold. However, since this value is not much larger than the manipulation threshold, it indicates that the risk of manipulation is generally low. However, the wide distribution of the score (Min:-66.671 to Max:64.294) and the high standard deviation (9.988) suggest that there is significant heterogeneity in financial reporting behaviour across clubs. The DSRI (Days Sales Receivable Index) mean of 1.196 is below the manipulation threshold but slightly above 1, and its wide range (0.134 – 11.215) and high standard deviation (1.251) suggest that football clubs exhibit significant variation in receivables management. This may be a sign that revenues may be inflated in some clubs. The mean of GMI (Gross Margin Index) is calculated as 1.668, which is above the manipulation threshold. However, the extremely wide distribution of the GMI (-121.461 – 131.560) and its high standard deviation (18.990) suggest that there are extraordinary fluctuations in clubs' gross margins. This finding may be due to the volatility of revenue sources (e.g. ticket sales, sponsorships) or inconsistencies in accounting policies in football clubs. The median value (0.986) is lower than the mean, suggesting that the distribution is skewed to the right and dominated by non-manipulative clubs. The mean of AQI (Asset Quality Index) was below the manipulation threshold with 1.128. However, the median (0.989) and relatively low standard deviation (0,659) suggest a general stability in asset quality. However, the maximum value of 5.661 suggests that some clubs may have proportionately increased intangible assets, which could be a potential indicator of manipulation.

Table 4. Descriptive Statistics

Whole Sample (N:126)	**Minimum**	**Maximum**	**Mean**	**Median**	**Std. Dev.**
DSRI	0.134	11.215	1.196	0.974	1.251
GMI	-121.461	131.560	1.668	0.986	18.990
AQI	0.194	5.661	1.128	0.989	0.659
SGI	0.499	3.284	1.223	1.115	0.503
DEPI	0.125	2.457	1.002	0.987	0.250
SGAI	0.384	29.681	1.418	1.080	2.614
LVGI	0.184	1.771	1.004	1.008	0.231
TATA	-0.458	0.356	-0.039	-0.027	0.166

Beneish M Score	**-66.671**	**64.294**	**-1.949**	**-2.658**	**9.988**
Manipulator Group (N:53)	**Minimum**	**Maximum**	**Mean**	**Median**	**Std. Dev.**
DSRI	0.486	11.215	1.654	1.200	1.779
GMI	-1.663	131.560	6.371	0.999	23.281
AQI	0.230	5.661	1.241	0.993	0.811
SGI	0.647	3.284	1.310	1.156	0.587
DEPI	0.707	2.457	1.019	0.980	0.254
SGAI	0.384	2.504	1.128	1.090	0.448
LVGI	0.486	1.458	0.941	0.974	0.198
TATA	-0.366	0.301	0.058	0.064	1.127
Beneish M Score	**-2.199**	**64.294**	**1.603**	**-1.406**	**11.860**
Non-Manipulator Group (N:73)	**Minimum**	**Maximum**	**Mean**	**Median**	**Std. Dev.**
DSRI	0.134	2.180	0.864	0.785	0.405
GMI	-121.461	1.388	-1.747	0.955	14.371
AQI	0.194	4.567	1.042	0.982	0.511
SGI	0.499	2.872	1.159	1.063	0.425
DEPI	0.125	1.923	0.989	0.990	0.247
SGAI	0.513	29.681	1.629	1.065	3.408
LVGI	0.184	1.771	1.049	1.042	0.243
TATA	-0.458	0.356	-0.109	-0.098	0.156
Beneish M Score	**-66.671**	**-2.234**	**-4.529**	**-3.396**	**7.455**

The SGI (Sales Growth Index) mean of 1.223 was below the manipulation threshold. While the mean value above 1 reflects a moderate increase in sales growth, the range (0.499 – 3.284) and standard deviation (0.503) indicate that growth rates are heterogeneous across clubs. This finding can be attributed to the competitive nature of the football industry and the fact that revenue growth varies from club to club. The DEPI (Depreciation Index) indicates a general stability in depreciation rates with a mean of 1,002 and a median of 0,987. The narrow distribution (0.125 – 2.457) and low standard deviation (0.250) suggest that clubs have limited tendency to make manipulative changes in their depreciation policies. The SGAI (Sales, General, and Administrative Expenses Index) mean of 1.418 is above the manipulation threshold, indicating an increase in administrative expenses, while the wide range (0.384 – 29.681) and high standard deviation (2.614) suggest that in some clubs these expenses grew uncontrollably or were manipulatively reduced. The median value (1.080) is lower than the mean, indicating that the distribution is skewed to the right and that a small number of clubs are pushing up the overall mean with extreme values. The fact that SGAI stands out in terms of manipulation implies that clubs may tend to overstate their earnings by controlling their selling, general and administrative expenses. For example, the maximum value reaching an extraordinary level of 29.681 suggests that some clubs have dramatically increased their administrative expenses or manipulatively underreported them compared to previous periods. This suggests that high operational costs (e.g. staff salaries, transfer expenditures) and pressure to generate revenue, which are common in the football sector, may lead clubs to ‘adjust’ their financial statements through SGAI. The LVGI (Leverage Index), with a mean of 1.004 and a median of 1.008, reflects a general balance in the indebtedness of football clubs. The narrow range (0.184 - 1.771) and low standard deviation (0.231) indicate that clubs are consistent in their use of financial leverage and the risk of manipulation is low in this variable. TATA (Total Accruals to Total Assets) has a negative mean value of -0.039. However, the width of the distribution (-0.458 - 0.356) and the standard deviation (0.166) suggest that there may be exceptions in some clubs where accruals are used for manipulative purposes.

In the Manipulator Group, the means of variables such as M Score, DSRI, GMI, SGAI and TATA indicate abnormal financial patterns associated with earnings manipulation. In particular, the high mean and standard deviation of DSRI (1.779) suggest that receivables may have been inflated relative to revenue growth, while the extreme variability in GMI (Std. Dev.: 23.281) suggests inconsistencies in gross margins. TATA's positive mean may be a clue to a manipulative use of accruals. In contrast, the relatively low averages of AQI, SGI, DEPI and LVGI suggest that these clubs are less prone to asset quality, sales growth, depreciation and leverage manipulation. In the Non-Manipulator Group, the mean Beneish M Score (-4.529) reveals a significantly lower risk of manipulation. The means of variables such as DSRI and TATA reflect a more consistent and transparent approach to financial reporting, while the negative mean and high standard deviation of GMI (14.371) suggest that some clubs may have unusual fluctuations in profitability. The high mean and standard deviation of the SGAI (3.408) suggest that administrative expenses may have increased for both manipulation and non-manipulation reasons (e.g. operational inefficiency). Overall, differences between manipulator and non-manipulator groups are evident in the DSRI, GMI and TATA variables, while other variables such as AQI, SGI and DEPI are less discriminative between groups. These findings imply that football clubs' earnings manipulation tendencies are concentrated in specific financial areas such as selling and administrative expenses, receivables management and accrual utilisation.

5. DISCUSSION

This study provides a comprehensive analysis of earnings manipulation risks in European football clubs using the Beneish M-Score model, revealing that 42% of the 126 club-year observations indicate manipulation risk, with SGAI emerging as the most manipulated variable (68 cases), followed by DSRI and TATA, while GMI is the least manipulated (17 cases). These findings reflect the unique financial dynamics of the football industry, where clubs face significant pressures from high operational costs, volatile revenue streams, and regulatory requirements such as UEFA’s Financial Fair Play (FFP) rules. The prominence of SGAI manipulation can be attributed to the discretionary nature of sales, general, and administrative expenses in football clubs. For instance, clubs may underreport administrative expenses, such as marketing or staff costs, or inflate sponsorship revenues to present a healthier financial position. The high variability in SGAI (standard deviation of 2.614) and extreme values (e.g., 29.681 for Porto in 2022) suggest that some clubs may engage in aggressive accounting practices to mask operational inefficiencies or meet stakeholder expectations, particularly under FFP constraints. This aligns with the football industry's tendency to prioritize short-term financial appearances to secure licensing, attract investors, or maintain competitive balance.

The significant manipulation patterns in DSRI and TATA further highlight sector-specific financial behaviors. DSRI, which measures the increase in receivables relative to sales, shows a mean of 1.196 and a high standard deviation (1.251), indicating variability in receivables management. Clubs may prematurely recognize revenues from transfer installments or sponsorship agreements, a common strategy to demonstrate compliance with FFP or to offset irregular cash flows. For example, the maximum DSRI value of 11.215 (Aalborg, 2020) suggests potential inflation of receivables, possibly driven by delayed payments in transfer deals. Similarly, TATA's positive mean in the manipulator group (0.058) indicates that some clubs report accounting profits without corresponding cash flows, likely through accruals related to transfer revenues or sponsorships. This practice is prevalent in an industry where high debt burdens and irregular revenue streams, such as match-day income, create incentives to project short-term financial health. The low manipulation in GMI (mean of 1.668, with a high standard deviation of 18.990) reflects the volatility of football clubs' revenue structures, driven by external factors like match performance or broadcasting deals, which may make manipulation in this area more detectable and thus less common.

The Beneish M-Score model's applicability to football clubs has both strengths and limitations. Its strength lies in its objective, ratio-based approach, which allows for a systematic assessment of manipulation risk across diverse clubs. The model's eight variables, particularly SGAI, DSRI, and TATA, effectively capture sector-specific manipulation tendencies, as evidenced by the significant differences between manipulator and non-manipulator groups. However, the model's reliance on financial ratios assumes a level of accounting standardization that may not fully account for the football industry's unique revenue streams (e.g., volatile match-day revenues, transfer fees) and expense structures (e.g., player salaries often reported separately from SG&A). This limitation may lead to false positives or negatives, particularly for clubs with irregular cash flows. For example, the high standard deviation in GMI (18.990) reflects the volatility in gross margins, which may be driven by external factors like match performance rather than manipulation, differing from findings in other sectors (e.g., Kamal & Ahmad, 2016). The study's focus on listed clubs ensures access to reliable financial data but limits its generalizability to unlisted clubs, which constitute a significant portion of European football. Additionally, qualitative factors such as corporate governance, which Dimitropoulos (2011) found to reduce manipulation, were not examined due to data constraints. The reliance on secondary data sources (e.g., Yahoo Finance, Investing) introduces potential inconsistencies in accounting practices across countries. Future research could address these limitations by incorporating unlisted clubs, qualitative governance metrics, or alternative models like the Jones model to validate findings.

6. CONCLUSION

This study aims to examine the risk of earnings manipulation in European football clubs from an international comparative perspective. The financial data of 18 listed clubs from 9 UEFA-affiliated leagues for the period 2018-2024 are analysed with the Beneish M-Score model and 126 club-year observations are conducted. The findings showed that 42% of the observations showed a risk of manipulation, with the highest risk occurring in 2018 (11 clubs). SGAI stood out as the most manipulated variable with 68 cases, while GMI was the least manipulated variable with 17 cases. DSRI and TATA stood out by exhibiting significant manipulation patterns.

The fact that SGAI is the most manipulated variable in football clubs can be attributed to the industry's high operational costs and pressure on revenue generation. Clubs face heavy financial burdens in items such as staff salaries, transfer expenditures and administrative expenses. The SGAI measures the change in the ratio of selling and administrative expenses to sales; therefore, the tendency for clubs to overstate earnings by understating expenses or inflating sales can make the SGAI susceptible to manipulation. For example, exaggeration of sponsorship deals or concealment of personnel costs can often be used as a strategy to ‘fix’ the financial statements through this variable. The least manipulation of GMI is thought to be due to the volatility of the revenue structure of football clubs. GMI tracks changes in gross profit margin; however, clubs' revenues (e.g. match-day revenues, broadcasting rights) can fluctuate depending on external factors, making manipulation difficult. Moreover, as gross profit margin directly reflects the core activities of clubs, manipulation in this area may make the lack of transparency more apparent and increase the risk of detection.

The fact that DSRI and TATA show significant patterns of manipulation can be explained by specific dynamics in the financial context of football clubs. The DSRI measures the increase in the ratio of receivables to sales. Clubs may prematurely recognise revenue by inflating receivables such as transfer instalments or sponsorship payments. This is a common method, especially under pressure to comply with regulations such as Financial Fair Play (FFP). TATA assesses the ratio of accruals to total assets; positive TATA values indicate increased accounting profit without cash flow. Football clubs can create an image of short-term financial health by overstating transfer revenues or sponsorships through accruals. This tendency can often be observed in an industry where clubs struggle with irregular cash flows and high debt burdens. In the context of these results, football clubs may be advised to increase transparency in administrative expense reporting and receivables management. Detailed breakdown of expense items should be made public to prevent SGAI manipulation, and receivables policies should be standardised to reduce DSRI risk. Stricter internal controls and compliance with FFP may deter manipulation. Furthermore, corporate governance practices should be strengthened; independent boards of directors should be established, stakeholder oversight should be added to financial reporting processes, and accountability of managers should be increased. These practices are expected to increase both financial transparency and stakeholder confidence.

The findings emphasise SGAI and DSRI as manipulation indicators, in line with studies such as Beneish (1999) and Tarjo & Herawati (2015). However, the low manipulation in GMI is different from the findings of Kamal & Ahmad (2016) on the sensitivity of gross profit margin, which can be explained by the revenue volatility of football clubs. Kokic, Gligoric & Knezevic (2018) find a manipulation rate of 31% in Serbian clubs, while our rate of 42% indicates a higher prevalence, which can be reconciled with the FFP incentive for clubs to manipulate as noted by Dimitropoulos, Leventis & Dedoulis (2016). Dimitropoulos (2011), on the other hand, argues that corporate governance reduces manipulation; the effect of this factor seems to be limited in the sample of this study.

This research contributes to the limited literature on the detection of earnings manipulation in football clubs by applying the Beneish M-Score model with an international sample. The results of the research are important for the managers of football clubs in terms of guiding them to develop transparency-oriented policies by identifying risky areas (SGAI, DSRI, TATA) in financial reporting processes. For investors in the sector, it is thought that it will enable them to make more informed investment decisions by evaluating the risks of manipulation. It is also hoped that this research will make a significant contribution to the field by emphasising the necessity of financial auditing in football. However, the study has shortcomings since it only covers clubs traded on the stock exchange and does not examine qualitative factors such as corporate governance. In future research, the sample can be expanded with unlisted clubs, qualitative factors such as corporate governance and sectoral regulations can be analysed and Beneish M-Score can be compared with alternatives such as Jones model.

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