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# USING NONFINANCIAL MEASURES TO IMPROVE FRAUD RISK ASSESSMENTS: OPPORTUNITIES AND LIMITATIONS

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***Abstract:*** *Previous research indicates a growing need to address the issue of fraudulent financial research. In addition to financial measures, non-financial measures are those that should be considered in the process of measuring the economic performance of the company. This research points to the importance of an integrated way of measuring the financial performance of a company in assessing the risk of fraud, which implies the application of non-financial performance measures together with financial ones. If there is a difference between non-financial measures and financial performance, this may be a warning sign that there may be a risk of fraud. Research on the application of non-financial measures in improving the risk assessment of fraud is scarce when looking at the Serbian context. Therefore, this research will add value to the existing literature on fraud risk management in financial statements.*

***Keywords:*** *non-financial measures, financial measures, risk, fraud, companies*

***JEL classification:*** *M41, M42, K42, Q19*

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# UPOTREBA NEFINANSIJSKIH MERA U UNAPREĐENJU PROCENE RIZIKA OD PREVARA: MOGUĆNOSTI I OGRANIČENJA

***Sažetak:*** *Prethodna istraživanja ukazuju na rastuću potrebu za bavljenje problematikom prevarnog finansijskog istraživanja. Pored finansijskih mera, i nefinansijske mere su te koje treba uzimati u obzir u procesu merenja ekonomskog učinka preduzeća. Ovo istraživanje ukazuje na značaj integrisanog načina u merenju finansijskih performansi komanije u proceni rizika od nastanka prevarnih radnji, što podrazumeva primenu nefinansijskih mera učinka zajedno sa finansijskim. Ukoliko postoji razlika između nefinansijskih mera i finansijskih performansi, to može da bude znak upozorenja da je moguće postojanje rizika od prevarne radnje. Istraživanja o primeni nefinansijskih mera u poboljšanju procene rizika od prevarnih radnji su oskudna kada se posmatra srpski kontekst. Stoga će ovo istraživanje dodati vrednost postojećoj literaturi za upravljanje rizikom od prevarnih radnji u finansijskim izveštajima.*

***Ključne reči:*** *nefinansijske mere, finansijske mere, rizik, prevarne radnje, kompanije*

## 1. INTRODUCTION

Fraudulent actions in the financial statements are most often carried out by the company's management. Ilter (2014) points out that the aggressiveness and endless passion of managers and owners can encourage them to commit various fraudulent acts. Various counterfeit transactions are entered into the business books, and in some cases without respecting the chronological order of business transactions. These problems require finding the most effective ways to manage the risk of fraudulent accounting actions (intentional misstatements in the financial statements). Supporting this statement is the fact that auditing standards are focused exclusively on the framework requirements for the assessment of material risks of misstatement in relation to audited financial statements (Kochinev, Antysheva, & Putintseva, 2020, p. 1).

The auditing profession is the one that guarantees the reliability of financial reports, which represent the information base for economic decision-making (Brown, Milašinović, Mitrović, & Knežević, 2020). Auditors make significant efforts to find an adequate methodology for effectively managing the risk of fraud. Financial measures are much more "affordable" for fraudulent activities, so non-financial measures available to auditors are favoured. For example, it is logical to expect that the growth of sales facilities will be positively correlated with the growth of revenue. Accounting standards themselves encourage the application of non-financial measures (Meyer, 2015), with the caveat that a special question is to what extent they are actually used by auditors in analytical procedures.

The paper is organized as follows. The first section is devoted to previous research on what their impact is on the design of the theoretical model concept in current research. The design and research procedures are described in the next section. Finally, the conclusion provides a summary and critique of the findings, after which areas for further research are identified. Then the results and discussion were presented. The limitations are then described and suggestions for future research are given.

## 2. BRIEF LITERATURE REVIEW

Performance measurement plays a crucial role when it comes to the development, implementation, and monitoring of a strategic plan of profit-oriented organizations (Teeratansirikool, Siengthai, Badir, & Charoenngam, 2013, p. 169). In order to form a comprehensive assessment of a company's business, it is indisputable that there is a need for multidimensional performance, such as non-financial and financial, as well as qualitative and quantitative. Previous research has identified conflicts in the application of performance measurement systems that include both financial and non-financial measures. The importance attached to analysts' non-financial information varied according to the industry in question. For example, when evaluating a company for the growth of high technology and services, analysts tend to attach more importance to nonfinancial data in their forecasts and recommendations (Low, & Siesfeld, 1997, p. 27).

Various corporate scandals underscore the need for investors to protect their investments at the earliest stages by distinguishing truths from misleading information. Stuart & Wang (2016) point out that politically affiliated companies are well positioned to perform manipulative accounting actions in relation to unrelated counterparties, and the reasons for this lie in the fact that such companies are less likely to be controlled by regulators, as well as that if their fraudulent actions are revealed, penalties for management will be delayed and perhaps reduced.

A large number of authors, among them: Erdoğan & Erdoğan, 2020; Omar, Johari, & Smith, 2017; Kaminski, Sterling Wetzel, & Guan, 2004; Kukreja, & Kumaraswamy, 2020; Amiram, Bozanic, Cox, Dupont, Karpoff, J., & Sloan, 2018; Bhasin, 2013; Dong, Liao, Fang, Cheng, Chen, & Wenjie, 2014; Rezaee, Ha, & Lo, 2014; Zhou & Kapoor, 2011; Persons, 1995; Milojević, Đurić, Maksimović, Rađenović, 2021; Knežević, Cvetković, Mićović, Mitrović, & Milojević, 2021, and many others, point out fraudulent financial reporting as one of the most important topics dealt with by regulatory bodies and agencies, and to the large presence of professional fraud in companies that negatively affected the quality of financial reports, which resulted in the manipulation of financial information, and which is ultimately a subject of serious economic concern due to the negative impact on the financial market, and the threat to the efficiency of the capital market.

Previous research indicating the importance of applying non-financial measures in identifying fraud in financial statements includes research by Brazel, Jones, & Zimbelman, 2009; Dechow, Ge, Larson, & Sloan, 2011; Ames, Brazel, Jones, Rich, & Zimbelman, 2012; Christopher, & Larcker, 1998 and many others. Non-financial measures are the leading guidelines when analysing and projecting financial performance. As types of non-financial measures for the mentioned purpose, customer satisfaction, number of employees, and square feet of operations stand out. It is important to mention Benchmarking with competitors as a method that uses financial as well as non-financial data comparing them with the average of the industry in which the observed company operates, with a leader in the industry, or with a carefully identified group of the related company's direct competitors.

Skousen, Jones, & Zimbelman (2009, p. 53) state that rapid asset growth, increased cash needs, and external financing are positively associated with the likelihood of fraud. Regardless of the fact that audit practice recognizes the importance of non-financial measures when assessing analytical procedures, auditors are currently not required to take into account non-financial measures (e.g., facility growth, number of outlets); (Brazil, Jones, & Zimbelman, 2009, p. 10.) For example, if a company rents lack of storage space for the amount of inventories that has registered in the balance sheet as part of current assets, it may indicate a warning signal that there is a risk of fraudulent actions. There are numerous instances in the real world that companies create fictitious stocks or record excessive income by manoeuvring their financial figures, in order to improve the company's financial performance so that shareholders gain a better business image of the company or for other reasons such as maintaining their management status raising the price of shares, more favourable conditions for existing financing (Repousis, 2016, p. 1064). The use of non-financial information is supported by the fact that this information is much more difficult to misuse in terms of hiding or falsifying it, and in some cases, it is easily available for download.

## 3. METHODOLOGY

The research in this paper was conducted on a sample of companies whose shares are listed on the Belgrade Stock Exchange within Sector A-Agriculture, Forestry and Fishing and which are registered with the Business Registers Agency under group 0111 - Growing of cereals (except rice), leguminous crops and oilseeds. Namely, out of 21 companies belonging to the mentioned group, whose shares were listed on December 31, 2020, on the Belgrade Stock Exchange, the survey covered 16. Two companies were not included in the survey because their financial statements stated that they did not have employees, while three companies did not have available financial reports on the official website of the Business Registers Agency of the Republic of Serbia. Obradović, Milašinović & Bogićević (2021) also point to the problem of the lack of publicly available financial reports of companies from the Belgrade Stock Exchange.

Statistical data processing was performed using the statistical package IBM SPSS Statistics Version 24. In order to determine whether there were statistically significant changes in the value of the used productivity indicators over time, the Friedman test was used. The mentioned test was used because the data deviate from the normal schedule. If the Friedman test determines the existence of statistically significant differences in the productivity of agricultural enterprises between the observed years, it is necessary to conduct subsequent testing. This retesting includes Wilcoxon's rank tests, with Bonferroni alpha correction to avoid type I error. Since labour productivity will be compared to the previous year (productivity in 2017 compared to 2016, in 2018 compared to 2017, and in 2019 compared to 2018), a new level of significance of 0.017 is obtained (i.e., the initial level of statistical significance of 0.05 is divided by 3) (Pallant, 2007). In order to monitor the trend of operating revenue and the number of employees and their comparison, base and chain indices were applied.

Table 1 shows the method of calculating the indicators used based on financial and operational data, which indicate productivity in relation to financial measures.

Table 1

*Indicators used and method of their calculation*

| Indicator | Calculation method |
|---|---|
| The ratio of operating revenue and the number of employees | Operating revenue / Number of employees |
| The ratio of sales revenue and the employees | Sales revenues / Number of employees |
| The ratio of EBITDA and the number of employees | EBITDA / Number of employees |
| The ratio of EBIT and the number of employees | EBIT / Number of employees |
| The ratio of net results and the number of employees | Net result / Number of employees |
| The ratio of operating assets and the number of employees | Business assets / Number of employees |
| EBITDA margin | EBITDA / Sales revenue |
| EBIT margin | EBIT / Sales revenue |
| Net profit rate | Net result / Sales revenue |
| ROA | Business result / Average value of business assets |
| ROE | Net result / Average value of capital |

*Note.* Author's illustration.

The indicators used in Table 1 are based on financial ratio analysis as one of the frequently used financial analysis techniques based on a combination of data from financial statements that have been officially disclosed.

## 4. RESEARCH RESULTS

The financial events of companies are reflected in the financial statements of companies. For the purposes of the research, the data from the Balance Sheet, Income Statement were used, and additional non-standardized financial measures (such as EBITDA) were calculated. In addition to financial measures, non-financial measures were also used. In order to see the (dis) proportionality in the movement of operating revenues and the number of employees for companies from Sector A-Agriculture, Forestry and Fishing for the four-year period 2016-2019, and their trend of changes by year and base year, Table 3 and Figures 1 and 2 are given:

Table 2

*Comparative presentation of operating income and number of employees from Sector A-Agriculture, Forestry, and Fishing for the period 2016-2019*

| Company | 2016 | | 2017 | | 2018 | | 2019 | |
|---|---|---|---|---|---|---|---|---|
| | Operating income (000 RSD) | Emp. No. | Operating income (000 RSD) | Emp. No. | Operating income (000 RSD) | Emp. No. | Operating income (000 RSD) | Emp No. |
| Agrobačka a.d. Bačka Topola | 175.047 | 54 | 114.947 | 54 | 150.739 | 44 | 93.015 | 43 |
| Bačka a.d. Sivac | 318.215 | 47 | 272.338 | 42 | 302.930 | 38 | 229.515 | 33 |
| Borac a.d. Šurjan | 546.504 | 28 | 523.864 | 32 | 472.367 | 32 | 584.249 | 32 |
| PP Feketić a.d. Sombor | 555.766 | 67 | 540.411 | 69 | 432.805 | 77 | 410.141 | 78 |
| Hajdučica a.d. Hajdučica | 527.651 | 54 | 577.351 | 50 | 469.959 | 53 | 674.777 | 56 |
| Irmovo a.d. Kisač | 155.469 | 19 | 30.161 | 18 | 174.899 | 17 | 107.726 | 13 |
| Lučić Prigrevica a.d. Novi Sad | 1.231.198 | 60 | 1.589.139 | 60 | 1.226.491 | 58 | 1.207.003 | 36 |
| Mitrosrem a.d. Srem. Mitrovica | 1.038.197 | 407 | 987.437 | 379 | 962.203 | 362 | 862658 | 192 |
| Nova Peščara a.d. Deliblata | 163.464 | 33 | 193.157 | 32 | 208.090 | 30 | 213.295 | 27 |
| Omoljica a.d. Omoljica | 190.340 | 30 | 122.348 | 30 | 164.469 | 30 | 14160 | 29 |
| PTK Panonija a.d. Panonija | 839.244 | 178 | 792.968 | 173 | 889.170 | 164 | 861.541 | 173 |
| PP Miletić a.d. Sombor | 567.176 | 80 | 542.742 | 79 | 516.659 | 82 | 473.561 | 85 |
| Sloga a.d. Banat. Karlovac | 51.601 | 5 | 80.704 | 3 | 56.327 | 25 | 40.608 | 1 |
| Sloga a.d. Kać | 243.105 | 41 | 141.460 | 43 | 208.691 | 42 | 132.397 | 40 |
| Stari Tamiš a.d. Pančevo | 1.675.513 | 192 | 1.611.729 | 194 | 1.389.812 | 190 | 1.507.150 | 190 |
| Vojvodina a.d. Sombor | 408.463 | 29 | 400.909 | 32 | 432.744 | 38 | 472.093 | 37 |

***Note. The authors, based on company financial statements.***

Table 3

*Base and chain indices of operating revenue per employee of companies from Sector A-Agriculture, Forestry and Fishing for the period 2016-2019*

| | *Base indices (100=2016)* | | | *Chain indices* | | |
|---|---|---|---|---|---|---|
| | **2017** | **2018** | **2019** | **2017** | **2018** | **2019** |
| Agrobačka a.d. Bačka Topola | 72,37% | 105,68% | 66,73% | 72,37% | 146,04% | 63,14% |
| Bačka a.d. Sivac | 95,77% | 117,74% | 102,72% | 95,77% | 122,94% | 87,24% |
| Borac a.d. Šurjan | 83,88% | 75,63% | 93,54% | 83,88% | 90,17% | 123,69% |
| PP Feketić a.d. Sombor | 94,42% | 67,76% | 63,39% | 94,42% | 71,77% | 93,55% |
| Hajdučica a.d. Hajdučica | 118,17% | 90,75% | 123,32% | 118,17% | 76,79% | 135,89% |
| Irmovo a.d. Kisač | 20,48% | 125,73% | 101,27% | 20,48% | 614,00% | 80,55% |
| Lučić Prigrevica a.d. Novi Sad | 129,07% | 103,05% | 163,39% | 129,07% | 79,84% | 158,55% |
| Mitrosrem a.d. Sremska Mitrovica | 102,14% | 104,20% | 176,14% | 102,14% | 102,02% | 169,04% |
| Nova Peščara a.d. Deliblata | 121,86% | 140,03% | 159,48% | 121,86% | 114,91% | 113,89% |
| Omoljica a.d. Omoljica | 64,28% | 86,41% | 76,83% | 64,28% | 134,43% | 88,91% |
| PTK Panonija a.d. Panonija | 97,22% | 114,99% | 105,62% | 97,22% | 118,29% | 91,85% |
| PP Miletić a.d. Sombor | 96,90% | 88,87% | 78,58% | 96,90% | 91,71% | 88,42% |
| Sloga a.d. Banatski Karlovac | 260,67% | 21,83% | 393,48% | 260,67% | 8,38% | 1802,33% |
| Sloga a.d. Kać | 55,48% | 83,80% | 55,82% | 55,48% | 151,04% | 66,61% |
| Stari Tamiš a.d. Pančevo | 95,20% | 83,82% | 90,90% | 95,20% | 88,05% | 108,44% |
| Vojvodina a.d. Sombor | 88,95% | 80,85% | 90,59% | 88,95% | 90,90% | 112,04% |

***Note. The authors, based on company financial statements.***

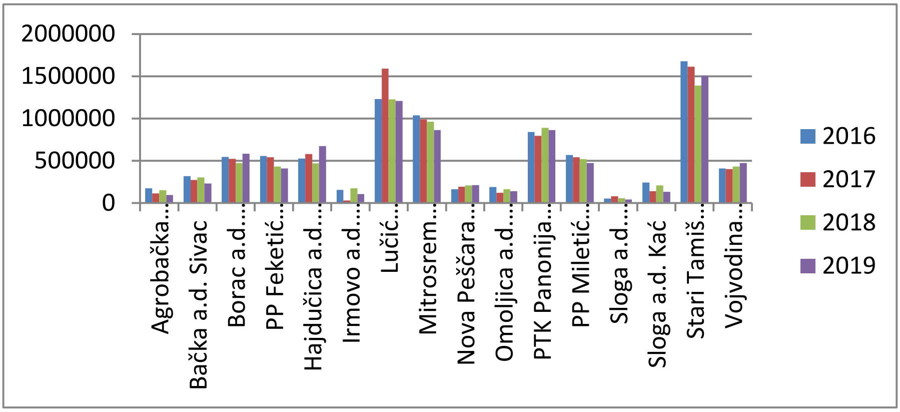


*Figure 1*. Trend of operating revenues of the observed companies from the Sector A-Agriculture, Forestry and Fishing for the period 2016-2019

*Note*. The authors, based on company financial statements.

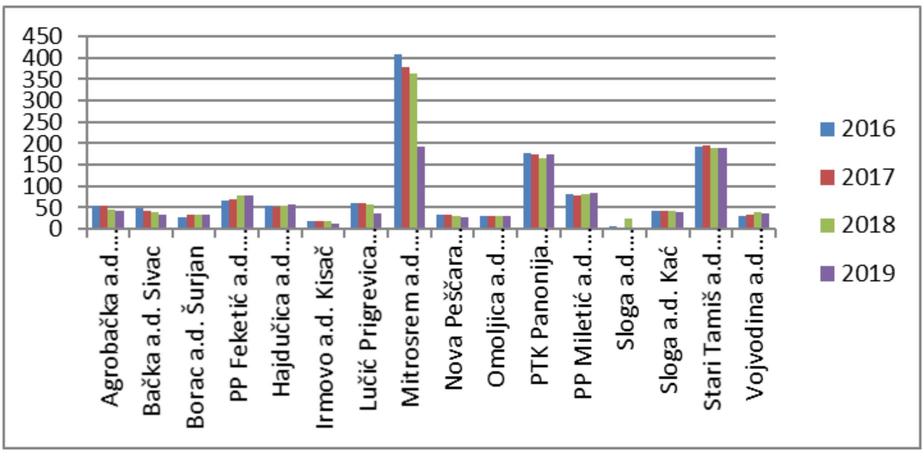


*Figure 1*. Movement of the number of employees of the companies from the Sector A- Agriculture, Forestry and Fishing for the period 2016-2019

*Note*. The authors, based on company financial statements.

In most cases, as revenues increase, the number of employees is likely to increase to some extent. The employee growth rate should follow the industry in which it is observed. Observing the movement of operating income and the number of employees in Figures 1 and 2 in the same time frame, it can be seen that there is a disproportion between the observed phenomena, which in some years is more, and in some less pronounced, observing individual companies in the sample. Special attention is drawn to the circumstance when sales revenues increase, and the number of employees decreases. Such occurrences should heighten the auditor's concerns. The number of employees is not the sole measure that could be used to measure performance and find gaps in the dynamics of movement (Ames et al., 2012, p. 23), but other non-financial measures are available to auditors such as product representatives, representatives by regions, number of distributors, number of customers and more.

Table 4 shows the descriptive statistics of employee productivity in the observed agricultural companies measured by sales revenue per employee in the period from 2016 to 2019.

Table 4

*Descriptive statistics of sales revenue per employee of the companies from Sector A-Agriculture, Forestry and Fishing for the period from 2016 to 2019*

| **Sales revenue / Employees** | **2016** | **2017** | **2018** | **2019** |
|---|---|---|---|---|
| Average values (000 RSD) | 8.517,69 | 8.540,26 | 7.197,52 | 9.879,86 |
| Median (000 RSD) | 6.777,25 | 6.202,06 | 6.258,62 | 7.185,73 |
| Max (000 RSD) | 20.392,25 | 26.080,73 | 18.141,16 | 32.678,44 |
| Min (000 RSD) | 2.492,37 | 231,17 | 1.397,12 | 1.708,98 |

*Note*. The authors, based on company financial statements.

As can be seen from Table 4, during the observed period, the average value of sales revenue per employee recorded a growth trend in the first two observed years, and after the decline in value in 2018, followed the increase in value. The maximum values of sales revenue per employee during the observed period are characteristic of one company. In 2017, six companies increased sales revenues per employee compared to 2016, while 10 companies saw a decline in value. In 8 companies, the value of sales revenue per employee was lower in 2018 compared to 2017, while in 8 companies there was an increase in value. Ten companies increased the value of sales revenue per employee in 2019 compared to 2018, while the remaining 6 had a lower value. The results of the Friedman test ($\chi 2$ (3, n = 16) = 4.056; p = 0.256) show that changes in sales revenue per employee during the observed period are not statistically significant.

Table 5 shows the descriptive statistics of employee productivity measured by EBITDA per employee in the period from 2016 to 2019.

Table 5

*Descriptive EBITDA statistics per employee of companies from Sector A-Agriculture, Forestry and Fishing for the period from 2016 to 2019*

| EBITDA/Employees | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|
| The average value (000 RSD) | -1.904,57 | 143,4 | 700,48 | 1,824.82 |
| Median (000 RSD) | 655,72 | 255,54 | 332,16 | 377,61 |
| Max (000 RSD) | 5.055,80 | 6.641,28 | 4.873,53 | 12.717,00 |
| Min (000 RSD) | - 48.478,00 | - 7.330,00 | - 2.029,36 | - 1.312,80 |
| The number of companies with negative productivity | 3 | 5 | 4 | 3 |
| The number of companies with positive productivity | 13 | 11 | 12 | 13 |

*Note*. The authors, based on company financial statements.

As can be seen from Table 5, the average value of EBITDA per employee records a growth trend in the observed time period. One company from the sample achieved the maximum value of this indicator in the first observed year, and in the remaining three years, it achieved the minimum values. More than 65% of companies had a positive value of EBITDA per employee during the observed period. Five companies increased the value of EBITDA per employee in 2017 compared to 2016, while in 11 companies this indicator is lower. In 2018, the value of EBITDA per employee compared to 2017 increased in 11 companies, while 5 companies recorded a lower value. At the end of 2019, ten companies increased the value of EBITDA per employee compared to 2018, while the remaining 6 companies recorded a lower value in the same time interval. These changes in EBITDA per employee during the observed time period are not statistically significant. This is indicated by the results of the conducted Friedman test ($\chi 2$ (3, n = 16) = 6.375; p = 0.095).

As shown in Table 6, the average value of productivity of employees in agricultural enterprises measured by EBIT per employee recorded a growth trend during the observed period. Namely, in the first two years, the average value had a negative value, and in the last two years, it had a positive value. The company that achieved the minimum values of EBIT per employee in the first three observed years, in 2019 achieved the maximum value of this indicator. In each observed year, less than 40% of enterprises had negative productivity measured by EBIT per employee. Four companies increased the value of EBIT per employee in 2017 compared to 2016, while in the remaining 12 there was a decrease in the value of this indicator. In nine companies, this indicator is higher in 2018 compared to 2017, while in 7 companies its value decreased. Further, nine companies in 2019 increased the value of EBIT per employee compared to 2018, while the remaining 7 companies recorded a lower value. However, the results of the conducted Friedman test ($\chi 2$ (3, n = 16) = 6.975; p = 0.073) show that the changes in the value of EBIT per employee during the observed period are not statistically significant.

Table 6

*Descriptive EBIT statistics per employee of the companies from Sector A-Agriculture, Forestry and Fishing for the period from 2016 to 2019*

| EBIT/Employee | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|
| Average values (000 RSD) | - 2.349,35 | - 417,65 | 271,78 | 1.307,03 |
| Median (000 RSD) | 327,85 | 46,1 | 134,98 | 97,93 |
| Max (000 RSD) | 4.106,18 | 5.657,53 | 3.851,03 | 12.527,00 |
| Min (000 RSD) | - 49.961,00 | - 10.287,67 | - 2.159,12 | - 1.863,30 |
| Number of companies with negative productivity | 3 | 6 | 6 | 6 |
| Number of companies with positive productivity | 13 | 10 | 10 | 10 |

*Note*. The authors, based on company financial statements.

Table 7 shows the descriptive statistics of the productivity of agricultural enterprises in the period from 2016 to 2019, measured by the Net result per employee.

Table 7

*Descriptive statistics of the Net results per employee of companies from Sector A-Agriculture, Forestry and Fishing for the period from 2016 to 2019*

| Net result / Employee | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|
| Average values (000 RSD) | 3.354,93 | - 644,08 | 83,73 | 1.644,42 |
| Median (000 RSD) | 323,13 | 56,77 | 117,07 | 80,91 |
| Max (000 RSD) | 50.760,60 | 680,99 | 1.334,18 | 26.362,00 |
| Min (000 RSD) | - 1.563,96 | - 10.030,00 | - 1.169,80 | - 2.036,85 |
| Number of companies with negative productivity | 3 | 5 | 5 | 3 |
| Number of companies with positive productivity | 13 | 11 | 11 | 13 |

*Note*. The authors, based on company financial statements.

After the decrease in the average value of Net results per employee in 2017 compared to 2016, a growth trend followed in the last two observed years. The company that achieved the maximum value of Net result per employee in the first and last year, recorded the minimum values of this indicator in the second and the third year. More than 65% of companies in each year had positive productivity measured by the Net result per employee. In 2017, 2018 and 2019, 9 companies increased their productivity measured by the Net result per employee compared to the previous year, while 7 companies decreased the value of this indicator compared to the previous year. The results of the conducted Friedman test ($\chi2$ (3, n = 16) = 0.825; p = 0.843) show that the change in productivity, measured by the Net result per employee, during the observed period is not statistically significant.

Table 8 shows the descriptive statistics of the productivity of agricultural companies in the period from 2016 to 2019 measured by Operating assets per employee.

Table 8

*Descriptive statistics of Operating assets per employee of companies from Sector A-Agriculture, Forestry and Fishing for the period from 2016 to 2019*

| Operating assets / Employee | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|
| Average values (000 RSD) | 30.734,24 | 36.044,32 | 26.172,98 | 64.454,31 |
| Median (000 RSD) | 17.964,64 | 20.253,75 | 20.975,83 | 23.272,42 |
| Max (000 RSD) | 120.523,60 | 198.133,00 | 70.951,34 | 540.892,00 |
| Min (000 RSD) | 8.875,18 | 9.166,65 | 8.747,84 | 8.051,51 |

*Note*. The authors, based on company financial statements.

The average value of productivity of the observed agricultural enterprises measured by Operating assets per employee varies during the observed time period. After the growth of the average value of operating assets per employee in 2017, there was a decline in value in 2018, and in the following year, there was new growth. The maximum value of the indicator Operating assets per employee in the first two observed years was achieved by one company. Further, one company recorded the minimum values of this indicator in 2018 and 2019. At the end of 2017, nine companies had a higher value of Operating Assets per employee compared to the end of 2016, while 7 companies recorded the opposite. Twelve companies increased their productivity in 2018 compared to 2017, while in 4 companies there was a decrease. In addition, in 2019, 12 companies increased their productivity compared to 2018, while for 4 companies the opposite was recorded. The results of the Friedman test ($\chi2$ (3, n = 16) = 15.075; p = 0.002) indicate that there is a statistically significant difference in the productivity of agricultural companies (measured by business assets per employee) during the observed four-year period. Wilcoxon's rank test found the existence of a statistically significant increase in Business Assets per employee in 2019 compared to 2018 (z=-2.876; p=0.004) with a large difference (r=0.51). The median Business assets per employee increased from

Md=20,957.83 (000 RSD) in 2018 to Md=23,272.42 (000 RSD) in 2019. Changes in the value of business assets per employee in 2017 compared to 2016 and in 2018 compared to 2017 are not statistically significant.

Table 9 shows the descriptive statistics of the EBITDA margin of agricultural companies in the period from 2016 to 2019.

Table 9

*Descriptive statistics of EBITDA margin of companies from Sector A-Agriculture, Forestry and Fishing for the period from 2016 to 2019*

| **EBITDA margin** | **2016** | **2017** | **2018** | **2019** |
|---|---|---|---|---|
| Average values | - 18,85% | - 4,11% | - 1,83% | 8,27% |
| Median | 9,43% | 4,80% | 5,38% | 7,12% |
| Max | 40,30% | 25,46% | 47.88% | 73.44% |
| Min | - 472,50% | - 55,11% | - 145,25% | - 51,50% |
| Number of companies with the negative EBITDA margin | 3 | 5 | 4 | 3 |
| Number of companies with the positive EBITDA margin | 13 | 11 | 12 | 13 |

*Note*. The authors, based on company financial statements.

As can be seen from Table 9, the average value of the EBITDA margin shows an upward trend. Thus, in the first three years, the negative average value of this indicator was recorded, and in the last observed year, it was positive. In each observed year, more than 65% of companies had a positive EBITDA margin. In four companies, the EBITDA margin is higher at the end of 2017 than at the end of 2016, while in 12 companies the opposite is true. Ten companies had higher EBITDA margins at the end of 2018 compared to the end of 2017, while six companies had a lower value of this indicator. In eight companies, the EBITDA margin is higher at the end of 2019 compared to the end of 2018, while for the same number of companies the opposite is true. These changes in the EBITDA margin during the observed four-year period are not statistically significant, as indicated by the results of the Friedman test ($\chi2$ (3, n = 16) = 7.188; p = 0.066).

Descriptive statistics of the EBIT margin of agricultural companies in the period from 2016 to 2019 are shown in Table 10.

Table 10

*Descriptive statistics of the EBIT margin of agricultural companies in the period from 2016 to 2019*

| EBIT margin | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|
| Average values | - 24,39% | - 22,70% | - 8,25% | 1,40% |
| Median | 5,89% | 0,75% | 1,85% | 1,50% |
| Max | 34,86% | 21,69% | 39,94% | 54,74% |
| Min | - 486,96% | - 225,93% | - 154,54% | - 63,05% |
| Number of companies with the negative EBIT margin | 3 | 6 | 6 | 6 |
| Number of companies with the positive EBIT margin | 13 | 10 | 10 | 10 |

*Note*. The authors, based on company financial statements.

The average value of the EBIT margin recorded a growth trend during the observed period (Table 10). In each of the observed years, more than 60% of companies had a positive EBIT margin. Three companies had a higher EBIT margin at the end of 2017 compared to the end of 2016, while 13 companies recorded a lower value. In 11 companies, this indicator is higher at the end of 2018 compared to the end of 2017, while in 5 companies the opposite was noted. Nine companies had a higher EBIT margin at the end of 2019 compared to the end of 2018, while it was lower in seven companies. The results of the conducted Friedman test ($\chi2$ (3, n = 16) = 7.831; p = 0.052) show that the change in EBIT margin during the observed period is not statistically significant.

The average value of the net profit rate decreased in 2017, compared to the first observed year, and in the last two years, there was an increase in value (Table 9). In each observed year, more than 65% of companies had a positive net profit rate. At the end of 2017, half of the companies had a higher net profit rate compared to the end of 2016, while the same number of companies recorded the opposite. Ten companies increased the net profit rate at the end of 2018 compared to the end of 2016, while 6 companies recorded a lower value of this indicator. At the end of 2019, 50% of companies increased the value of the net profit rate compared to the end of 2018, while the same number of companies saw a decrease in the value. However, the stated changes in the net profit rate over time are not statistically significant, as indicated by the results of the conducted Friedman test ($\chi2$ (3, n = 16) = 2.978; p = 0.395).

Table 11

*Descriptive statistics of the net profit rate of companies from Sector A-Agriculture, Forestry and Fishing for the period 2016-2019*

| Net profit rate | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|
| Average values | 31,81% | - 10,95% | - 4,65% | 0,94% |
| Median | 3,35% | 0,95% | 1,48% | 1,29% |
| Max | 494,75% | 11,83% | 26,79% | 107,24% |
| Min | - 23,37% | - 73,97% | - 83,73% | - 58,90% |
| The number of companies with the negative net income | 3 | 5 | 5 | 3 |
| Number of companies with the positive net profit rate | 13 | 11 | 11 | 13 |

*Note*. The authors, based on company financial statements.

Table 12 shows the descriptive statistics of the rate of return on operating assets in agricultural companies in the period from 2016 to 2019.

Table 12

*Descriptive statistics of the rate of return on operating assets in agricultural companies in the period from 2016 to 2019*

| ROA | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|
| Average values | 1,68% | - 0,19% | 0,34% | 1,07% |
| Median | 2,93% | 0,29% | 1,11% | 0,56% |
| Max | 16,73% | 8,05% | 11,17% | 10,47% |
| Min | - 27,83% | - 12,52% | - 12,28% | - 12,68% |
| Number of companies with the negative ROA | 3 | 6 | 6 | 6 |
| Number of companies with the positive ROA | 13 | 10 | 10 | 10 |

*Note*. The authors, based on company financial statements.

As can be seen from Table 12, the average value of the rate of return on operating assets recorded fluctuations over time. Thus, after the first year, there is a decrease in value, and in the last two observed years, there has been an increase in this value. The minimum value of ROA in all four observed years was achieved by one company. Further, Table 10 shows that in each year, most companies achieved a positive rate of return on operating assets. At the end of 2017, four companies achieved a higher rate of return on operating assets compared to the end of 2016, while the decrease was recorded in 12 companies. In the case of 7 companies, the rate of return on operating assets is higher at the end of 2018 compared to the end of 2017, while in 9 companies it is the opposite. At the end of 2019, half of the companies had a higher value of ROA compared to the end of 2018, while the same number of companies had a lower value. The results of the conducted Friedman test ($\chi2$ (3, n = 16) = 8,771; p = 0,032) indicate that changes in the rate of return on operating assets are not statistically significant.

Table 13 shows descriptive statistics on the rate of return on equity in the period from 2016 to 2019.

Table 13

*Descriptive statistics on ROE on capital in the period from 2016 to 2019*

| ROE | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|
| Average values | 14,67% | - 0,18% | 0,92% | 1,60% |
| Median | 2,31% | 0,62% | 1,41% | 0,99% |
| Max | 187,66% | 9,71% | 16,29% | 16,34% |
| Min | - 6,04% | - 14,42% | - 13,55% | - 11,99% |
| Number of companies with the negative ROE | 3 | 5 | 5 | 3 |
| Number of companies with the positive ROE | 13 | 11 | 11 | 13 |

*Note*. The authors, based on company financial statements.

As in the case of ROA, the average value of ROE decreased in 2017, followed by an increase in value. Further, in each year, most companies achieved a positive return on equity. At the end of 2017, 7 companies achieved a higher return on equity compared to the end of 2016, while 9 companies saw a decrease in return. Nine companies increased the rate of return on equity in 2018 compared to 2017, while 7 companies saw a decline in the value of this indicator. In 2019, half of the companies increased their return on equity compared to the end of 2018, while the same number of companies saw a decrease in value. However, the results of the Friedman test ($\chi2$ (3, n = 16) = 5.356; p = 0.148) indicate that changes in the rate of return on equity are not statistically significant during the observed period.

## 5. CONCLUSION

The review of the academic and professional literature suggests that a larger number of papers dealing with the application of non-financial measures in combination with financial measures are needed to identify fraudulent actions in mofinancial statements.

The importance of non-financial information that comes from sources that are independent, and therefore valid, is great for detecting fraud with financial statements. The reason for that is that it is unlikely that as such they will be the subject of manipulative actions. This is supported by the situations when non-financial measures of companies that deal with fraudulent activities do not follow the growth of their financial performance. It is suggested that auditors should make greater use of non-financial measures to assess the likelihood of fraudulent financial reporting, and in this context suggests testing performance indicators based on financial data for auditors in applying analytical procedures, which would ultimately increase the quality of financial reporting and thus valid information platforms for decision-making of various interest groups. Therefore, the academic community and the profession are encouraged to develop a theoretical model that will deal with the selection and use of key performance measurement criteria through a combination of financial and non-financial measures, with special reference to detecting fraud signals. The limitation is the unavailability of many non-financial measures, which, unlike the financial measures in the financial statements, have not been made public.

The authors hope that the information from this research will be useful in developing financial performance metrics based on non-financial measures, which would encourage wider academic attention to this issue.

## REFERENCE

Ames, D., Brazel, J. F., Jones, K. L., Rich, J. S., & Zimbelman, M. F. (2012). Using Nonfinancial Measures to Improve Fraud Risk Assessments. *Current Issues in Auditing*, *6*(1), 28–34. doi:10.2308/ciia-50168.

Amiram, D., Bozanic, Z., Cox, J. D., Dupont, Q., Karpoff, J., & Sloan, R. (2018). Financial reporting fraud and other forms of misconduct: A multidisciplinary review of the literature. *Review of Accounting Studies*, *23*(2), 732-783.

Bhasin, M. L. (2013). Corporate Accounting Fraud: A Case Study of Satyam Computers Limited. *Open Journal of Accounting*, *2*(2), 26-38. doi: 10.4236/ojacct.2013.22006.

Brazel, J. F., Jones, K. L., & Zimbelman, M. F. (2009). Using nonfinancial measures to assess fraud risk. *Journal of Accounting Research*, *47*(5), 1135–1166.

Brown, A., Milašinović, M., Mitrović, A., & Knežević, S. (2020). Are audit opinions related to bancruptcy forecasting of companies listed on the Sector A-Agriculture, forestry and fisheries? *Fresenius Environmental Bulletin*, *29*(11), 9899-9905.

Christopher D. I. & Larcker, D. F. (1998). Are Nonfinancial Measures Leading Indicators of Financial Performance? An Analysis of Customer

Satisfaction Reviewed work(s): *Journal of Accounting Research*, *36*, 1-35.

Dechow, P. M., Ge, W., Larson, C. R. and Sloan, R. G. (2011). Predicting material accounting misstatements. *Contemporary Accounting Research*, *28*(1), 17–82.

Dong, W., Liao, S. S., Fang, B., Cheng, X., Chen, Z., & Wenjie, F. (2014). The detection of fraudulent financial statements: an integrated language model. PACIS 2014 Proceedings. 383. Available at: http://aisel.aisnet.org/pacis2014/383.

Erdoğan, M., & Erdoğan, E. O. (2020). Financial Statement Manipulation: A Beneish Model Application. In *Contemporary Issues in Audit Management and Forensic Accounting* (pp.173-188), doi:10.1108/s1569-375920200000102014.

Ilter, C. (2014), Misrepresentation of financial statements: An accounting fraud case from Turkey. *Journal of Financial Crime*, *21*(2), 215-225. https://doi.org/10.1108/ JFC-04-2013-0028.

Kaminski, K. A., Sterling Wetzel, T., & Guan, L. (2004). Can financial ratios detect fraudulent financial reporting? *Managerial Auditing Journal*, *19*(1), 15-28. Available at: https://doi.org/10.1108/02686900410509802.

Knežević, S., Cvetković, D., Mićović, M., Mitrović, A., & Milojević, S. (2021). Analysis of the Presence of Criminal Offenses in the Field of the Shadow Economy in Serbia. *Lex localis - Journal of Local Self-Government*, *19*(1), 131-147.

Kochinev, Y., Antysheva, E., & Putintseva, N. (2020). Formalization of Analytical Procedures for Assessing the Risks of Material Misstatement in Financial Statements due to Fraud. In *Proceedings from International Scientific Conference on Innovations in Digital Economy* (pp. 1-5). Available at: https://doi.org/10.1145/3444465.3444532.

Kukreja, G., Gupta, S. M., Sarea, A. M., & Kumaraswamy, S. (2020). Beneish M-score and Altman Z-score as a catalyst for corporate fraud detection. *Journal of Investment Compliance*, *21*(4), 231-241. https://doi.org/10.1108/JOIC-09-2020-0022.

Low, J., & Siesfeld, T. (1997). Measures that matter: Non-Financial Performances. *Strategy & Leadership.* Emerald Backfilles.

Meyer, C. (2015). Pay attention to nonfinancial measures when performing audits. *Journal of Accountancy*, 14. Available at:

https://www.journalofaccountancy.com/newsletters/2015/sep/nonfinancial-measures-when-performing-audits.html.

Milojević, S., Đurić, O., Maksimović, D., & Rađenović, I. (2021). Monitoring of expenditure and revenue and fraudulent financial reporting. In *Education and Social Sciences Business and Economics* (p. 3). International Academic Institute, Skopje, Republic of N. Macedonia.

Noviarty, H., Puspitasari, A., & Heniwati, E. (2021). Do Internal Auditor and Audit Committee Have Impact on Audit Report Lag for Mining Industry? *Jurnal Akuntansi dan Keuangan*, *23*(1), 15-23. doi: 10.9744/jak.23.1.15-23.

Obradović, V., Milašinović, M., & Bogićević, J. (2021). Segment disclosures in the financial statements of stock companies in the Republic of Serbia and the Republic of Croatia. *Ekonomski horizonti, 23*(1), 55-70. https://doi.org/10.5937/ ekonhor2101055O.

Omar, N., Johari, Z., & Smith, M. (2017). Predicting fraudulent financial reporting using artificial neural network. *Journal of Financial Crime, 24*(2), 362-387. https://doi.org/10.1108/JFC-11-2015-0061.

Pallant, J. (2007). *SPSS Survival Manual: A step by step guide to data analysis using SPSS for Windows.* Open University Press.

Persons, O. S. (1995). Using Financial Statement Data to Identify Factors Associated with Fraudulent Financial Reporting. *Journal of Applied Business Research* (JABR), *11*(3), 38-46. https://doi.org/10.19030/jabr.v11i3.5858.

Repousis, S. (2016). Using Beneish model to detect corporate financial statement fraud in Greece. *Journal of Financial Crime*, *23*(4), 1063–1073. doi:10.1108/jfc-11-2014-0055.

Rezaee, Z., Ha, M., & Lo, D. (2014). China Needs Forensic Accounting Education. *Open Journal of Social Sciences*, *2*, 59-65. doi:10.4236/jss. 2014.25013.

Skousen, C. J., Smith, K. R., & Wright, C. J. (2009). Detecting and predicting financial statement fraud: The effectiveness of the fraud triangle and SAS No. 99. In M. Hirschey, K. John, & A. K. Makhija (Eds.) *Corporate Governance and Firm Performance* (pp. 53-81). Emerald Group Publishing Limited. https://doi.org/10.1108/S1569-3732(2009)0000013005.

Stuart, T., & Wang, Y. (2016). Who cooks the books in China, and does it pay? Evidence from private, high-technology firms. *Strategic Management Journal*, *37*(13), 2658–2676. doi:10.1002/smj.2466.

Teeratansirikool, L., Siengthai, S., Badir, Y., & Charoenngam, C. (2013). Competitive strategies and firm performance: the mediating role of performance measurement. *International Journal of Productivity and Performance Management*, *62*(2), 168–184. doi:10.1108/17410401311295722.

Zhou, W. & Kapoor, G. (2011). Detecting evolutionary financial statement fraud. *Decision Support Systems*, *50*(3), 570-575, https://doi.org/10.1016/j.dss.2010.08.007.

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