# Impact of Business Intelligence Systems on Profitability: An Empirical Study

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**Abstract**: There is a research gap regarding the impact of Business Intelligence (BI) implementation on banks' profitability ratios. In particular, this relates to the financial profitability ratios of banks operating under the conditions of the Polish economy after 2015. The main research problem addressed in this study is whether the implementation of Business Intelligence systems has a positive impact on the profitability indicators of commercial banks. The main hypothesis formulated is that the use of a Business Intelligence management system between 2009 and 2020 improves the profitability of Polish commercial banks. The First Differences Generalized Method of Moments (FDGMM) panel dynamic model estimation method was used to evaluate this impact. The parameters of the models based on financial indicators were calculated for each of the selected indicators, and the analysis used those models for which the lagged BI variable, related to the timing of system implementation, proved statistically significant. Based on the obtained parameters of the models, long-term multipliers were calculated. The study determined the probability of the impact of using the business intelligence system on the selected indicators. The study was conducted on a group of the five largest out of the thirteen commercial banks listed on the Warsaw Stock Exchange in 2020. The assets of the surveyed banks comprise 50% of the assets of commercial banks in Poland. The study identified the impact of BI system use on selected profitability indicators of commercial banks. The generalized results of the study enable us to identify causal relationships between the use of the BI system in commercial banks and profitability, as measured by ROE and ROA. The research implications of this study may suggest to top management that implementing business intelligence systems can benefit the organization.

**Keywords**: Business intelligence,Impact of business intelligence, Financial condition, Bank

## 1. Introduction

Business Intelligence (BI) systems have become an integral part of conducting business in the 21st century. This is primarily due to the increasing need for organizations to analyze, interpret, and process data. A BI system proves to be helpful in fulfilling these tasks. Business Intelligence refers to the concept of utilizing an information system to gather and process information, enabling accurate business decision-making. Its purpose is to support and streamline decision-making processes, ultimately enhancing organizational efficiency (Hussinki, 2022). However, it is important to note that the implementation of a BI system alone does not guarantee satisfactory results. The key to success lies in a series of decisions aimed at improving the organization based on the insights obtained from the BI system (Tunowski, 2019).

In Poland, studies of the impact of business intelligence system on the profitability of commercial banks have not been widely reported so far. In the literature, it is hard to find cross-sectional studies of the impact of BI use on the profitability of commercial banks in Poland. The published works refer to individual cases of BI implementation in individual banks, without using statistical methods that allow generalization of research results. In terms of cross-sectional studies, the exception is the publication (Tunowski, 2019) which is based on data up to 2015, where no impact of the BI system on 2 of the 3 profitability indicators (ROE, operating profit margin) was found. A partial, positive impact was confirmed for the ROA indicator. Thus, the author notes that there is a research gap regarding the impact of BI implementation on banks' profitability ratios. In particular, it relates to the financial profitability ratios of banks operating in the conditions of the Polish economy with respect to the period after 2015. Filling the outlined research gap is a challenge for this study, the statistical method would be used to aim that goal.

The main research problem of this study is to investigate the impact of implementing Business Intelligence systems on the profitability of commercial banks in Poland. The study aims to test the following main hypothesis:

> *H0: The use of a Business Intelligence management system between 2009 and 2020 improves the profitability of Polish commercial banks.*

The paper specifically chooses the Return on Equity (ROE) and Return on Assets (ROA) indicators, which are widely recognized and extensively discussed in the literature (Almaqtari et al., 2019; Al-Homaidi et al., 2020). These indicators provide valuable insights into the financial performance of banks. Furthermore, the selection of commercial banks as the focus of the study is justified by their significant role in the economy. Banks serve as a crucial component of the economic system, acting as a vital "lifeline" that supports the proper functioning of various elements within the modern economy (Jaworski, J., Czerwonka, L., 2022). The performance of banks has a direct impact on the pace and quality of development for other enterprises, as well as accessibility to banking services and products. Any dysfunctionality within the banking sector can lead to severe crisis consequences, as evidenced by the financial market turbulence and economic difficulties experienced during the 2008-2009 crisis following the collapse of Lehman Brothers in September 2008 (Coleman, Feler, 2015). Therefore, it is crucial to explore solutions that can support bank management, including the adoption of modern Business Intelligence systems.

The second and third parts describe the selection of research objects (commercial banks) and provide a detailed discussion on the research method, specifically using the FDGMM dynamic panel model. Special attention was given to the model's form, incorporating the BI dichotomous variable to indicate the implementation of the BI system. Additionally, the verification method for the estimated models was thoroughly discussed.

In the Findings section, the results of the empirical study using the previously discussed method are presented. The results are also compared with the average levels of ROE and ROA as well as their average percentage increase, so that the obtained results can be correctly interpreted. The summary and discussion section confirms the hypothesis of a positive impact of the BI system on profitability indicators in polish commercial banks. However, a number of limitations of the study were also pointed out, which the author is aware of. Further directions of the study were also indicated, which, from the author's point of view, will be an interesting development of the obtained results. In the last part, possible practical use of the results of the study is indicated.

## 2. Method of Selection of Research Objects

The study included a selection of commercial banks (N objects) based on the following criteria. The banks had to operate as commercial banks and be listed on the Warsaw Stock Exchange at the end of 2022. These banks provided financial statements on a quarterly basis, which was necessary to obtain the required number of observations. Additionally, the selection was narrowed down to banks that publicly disclosed information about the implementation date of their business intelligence (BI) system for business analytics. Banks without this information were excluded from the study, as it was assumed that despite the lack of public disclosure, they likely had a business intelligence system.

Based on the above criteria, five banks were chosen. Two of these banks had a BI system in place before 2009, while the remaining three implemented it between 2009 and 2020. The selected banks represented approximately 50% of the assets in the commercial bank sector in Poland. The study utilized quarterly data from 2009 to 2020, spanning a total of 44 periods (quarters).

## 3. Methodology

Panel models are econometric models that are estimated using panel data. In the context of modern econometrics, "panel data" refers to data formed by combining time series observations (T periods) with cross-sectional observations for multiple objects (N objects) (Osińska, Kośko, Stempińska, 2007). Dynamic panel models assume that the formation of the dependent variable (Y) is influenced by lagged values of the dependent variable itself, the explanatory variables (X), and additional unobservable factors that are constant over time but specific to each group. These group-specific factors are known as group effects. Due to the time constancy of these group effects, different estimation methods are required for dynamic panel models compared to static models. In the literature, three main methodologies have been proposed: the Instrumental Variables Method (Anderson, Hsiao, 1981; Anderson, Hsiao, 1982), the Maximum Likelihood Method (Hsiao, 2003), and the Generalized Method of Moments (GMM).

The Generalized Method of Moments (GMM), specifically the First Differences Generalized Method of Moments (FDGMM) introduced by Arellano and Bond (1991), is one of the most widely used methods for estimating panel dynamic models. In this study, the FDGMM method is employed to estimate the panel dynamic models.

The idea of the FDGMM method can be described in the following steps (Dańska-Borsiak, 2009):

- 1. first differences model is calculated to remove time fixed group effects,
- 2. in the next step, the explanatory variables in the first differences model are replaced by instruments, which are the levels of variables lagged by two or more periods,

- 3. then the estimators of structural parameters are obtained by applying GMM to the first differences model.

The general form of the dynamic panel model is as follows (Dańska-Borsiak, 2009):

$$y_{it} = \gamma y_{i,t-1} + X_{it}^{T}\beta + \propto_i + \varepsilon_{it} \quad i = 1, \ldots, N,\ t = 1, \ldots, T. \tag{1}$$

where $X_{it}^{T}$ is a vector of explanatory variables (in the article it will be the dichotomous variable BI), $\beta$ is a vector of parameters, the same for all I and t. $\propto_i$ o signifies a group effect, random or non-random, while the random component has a normal distribution $\varepsilon_{it} \sim N(0, \sigma_{\alpha}^{2})$ for all i, t.

When studying the relationship between the financial profitability of banks and BI, it was assumed that the cross-sectional data would be the profitability ratios calculated for individual banks included in the panel. Temporal data are observed at a quarterly frequency. Taking into account the criterion of the number of observations (dozens) and the number of objects (several), the panel data belong to the category of macro-panels. The paper will use a model in which $X_{it}^{T}$ is a dichotomous variable (in level and latency). This variable is labeled BI and will take the following values:

1 - in quarters in which the bank had a business intelligence system,

0 - in quarters in which the BI system was not used.

Methods using lagged dichotomous explanatory variables in combination with dynamic panel models have already been described in the literature by Lachenmaier and Rottmann (2011) and by Ryamond, Mohnen, Mairesse, and Palma (2015). The dynamic panel model for the period takes the form:

$$y_{it} = \gamma y_{i,t-1} + BI_{i,t}\beta + BI_{i,t-1}\beta + \ldots + BI_{i,t-12}\beta + \propto_i + \varepsilon_{it} \tag{2}$$

where i = 1, …, N, t = 1, …, T = 12, N – the number of facilities (banks), T - the number of quarters, and the explanatory variable Y represents one of the two selected profitability indicators.

As a result, an attempt was made to estimate two econometric models - a separate one for each of the two indicators under analysis (ROE and ROA) in 2009 - 2020. The parameters of the models estimated in cases for which the lagged BI variable turned out to be statistically significant. When the BI variable with the largest lag turned out to be statistically insignificant, then this variable was omitted and a new model with a lagged BI variable smaller by a unit was estimated. Based on the obtained parameters of the models, long-run multipliers were calculated according to the following formula (Ossowski 2007):

$$\text{Long} - \text{term multiplier} = \frac{\beta_0 + \beta_1 + \cdots + \beta_i}{1 - \gamma_0} \qquad i = 1, \ldots, N \tag{3}$$

The interpretation of the above long-run multiplier is as follows: if the long-run level of the BI variable increases by a unit, this corresponds to a change in the long-run level of the selected financial indicator by the value of the long-run multiplier. After the estimation of the parameters of the panel model was completed, the procedure for verifying its statistical properties was carried out. For this purpose, the Sargan test and the test for autocorrelation of the increments of the residual component were used. The Sargan test examines whether the instruments in the estimation method were properly selected. Testing the properties of the GMM model is based on testing whether the instruments are appropriate, that is, uncorrelated with the random components. The null hypothesis of the Sargan test is that the instruments have been properly selected, while the alternative hypothesis is that the selection of instruments is incorrect. Using the probability value p-value, a result greater than the accepted level of significance means that there is no basis for rejecting the null hypothesis and thus authorizes the conclusion that the instruments were selected correctly (Tunowski, 2019).

The second diagnostic test of the models will be the Arellano-Bond test examining the presence of autocorrelation of the random component. The test answers the question of whether the instruments used during estimation are appropriate or, in other words, whether the conditions of moments are satisfied or not (Dańska-Borsiak, 2009). In the course of the study, the result of the test was calculated for first-order and second-order autocorrelation. However, from the point of view of the first-difference model, the test for second-order autocorrelation is important. First-order autocorrelation in a first-differences model is an expected phenomenon, while the occurrence of autocorrelation of an order higher than 1 in a first-differences model means that the conditions of moments are not met, so the instruments used in GMM estimation are not appropriate (Dańska-Borsiak, 2009).

The null hypothesis of the Arellano-Bond test is that autocorrelation does not occur (Mileya, 2007). Translating this into desirable p-values, they should be greater than 0.1; 0.5 and 0.01, respectively, depending on the level of significance adopted - the paper adopts a designation for three levels of significance: *** - significance of 1%, ** - significance of 5%, * - significance of 10%.In this case, there are no bases for rejecting the null hypothesis thus stating that autocorrelation does not occur. In conclusion, on the basis of the results obtained by the method of dynamic panel models, it will be possible to determine the probability of impact (its statistical significance) of the implementation and use of a business intelligence system on selected profitability indicators, as well as the long-term impact of BI implementation on a given financial profitability indicator (values calculated using the long-term multiplier) (Tunowski, 2019).

## 4. Findings

The estimated parameters of the dynamic panel models are reported in Table 1, focusing on selected profitability indicators, namely Return on Equity (ROE) and Return on Assets (ROA). The columns representing the financial profitability indicators correspond to the parameters of the model, which were estimated using the FDGMM method as described earlier.

**Table 1: The Impact of Business Intelligence System Implementation on Commercial Banks Profitability Indicators - FDGMM Method Using Dynamic Panel Model**

| | Return on equity (ROE) (model 1) | | Return on assets (ROA) (model 2) | |
|---|---|---|---|---|
| Y (lag Q1) | 0,0793 | | 0,1454 | *** |
| BI | -0,0024 | *** | -0,0005 | *** |
| BI (lag Q1) | -0,0012 | *** | -0,0001 | *** |
| BI (lag Q2) | 0,0063 | *** | 0,0010 | *** |
| BI (lag Q3) | -0,0070 | *** | -0,0009 | *** |
| BI (lag Q4) | 0,0014 | | -0,0003 | |
| BI (lag Q5) | 0,0013 | | 0,0005 | |
| BI (lag Q6) | -0,0067 | | -0,0012 | |
| BI (lag Q7) | -0,0005 | | 0,0000 | |
| BI (lag Q8) | 0,0033 | ** | 0,0005 | *** |
| BI (lag Q9) | 0,0033 | *** | 0,0005 | *** |
| BI (lag Q10) | -0,0094 | *** | -0,0010 | ** |
| No. of observations | 144 | | 140 | |
| Sargan test - value (degrees of freedom) | 147,555 (132) | | 143,411 (128) | |
| Sargan tets - p-Value | 0,168 | | 0,166 | |
| Autocorrelaction test AR (1) - value | -1,220 | | -1,220 | |
| Autocorrelaction test AR (1) - p-Value | 0,222 | | 0,222 | |
| Autocorrelaction test AR (2) - z value | 0,747 | | 0,747 | |
| Autocorrelaction test AR (2) - p-Value | 0,455 | | 0,455 | |
| Long-term multiplier | -0,012545977 | | -0,001793044 | |

*** - significance 1%, ** - significance 5%, * - significance 10%

Source: own elaboration.

The model estimated by the FDGMM method is characterized by a number of parameters that require explanation before proper interpretation. Y (lag 1) is the parameter standing next to the lagged Q1 of the explanatory variable, i.e. the selected ROE or ROA. The variables BI, BI (lag Q1), BI (lag Q2), etc. are the parameters standing by the BI variable and its lags. The number of observations means the number of observations that was used in the estimation of a particular model. Sargan test value (degrees of freedom) is the value of the Sargan test statistic along with the number of degrees of freedom in parentheses and along with the significance rating by the number of asterisks (*** - 1% significance, ** - 5% significance, * - 10% significance). Sargan p-Value, on the other hand, is the p-value for the Sargan test.

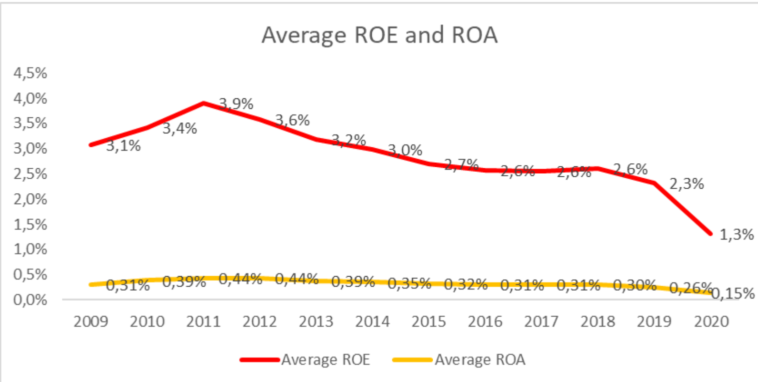
The next designations are for 1st and 2nd order autocorrelation tests. Autocorrelation test AR (1) value is the p-value of the first-order autocorrelation test statistic along with the significance rating by the number of stars (*** - 1% significance, ** - 5% significance, * - 10% significance). In turn, AR (1) p-Value - the p-value of the test for first-order autocorrelation. Similarly, Autocorrelation test AR (2) value denotes the p-value of the test statistic for second-order autocorrelation, along with the significance rating by the number of stars (*** - significance of 1%, ** - significance of 5%, * - significance of 10%). AR (2) p-Value refers to the p-value of the test for second-order autocorrelation. The last indicator is the long-run multiplier, which denotes the value of the long-run multiplier.

Diagnostic tests for both models on ROE and ROA profitability ratios are positive. This applies to both the Sargan test and the test for second-order autocorrelation. This demonstrates the proper choice of instruments in the estimation method used. Note that the statistically significant parameters at the BI variable are those standing at the lagged BI variable, which would indicate the lagged effect of the business intelligence system on the level of the profitability index. The statistical significance of the lagged BI variables indicates the impact of the system 1 year after implementation (Q1-Q3 quarters) and 3 years after BI system implementation (Q8-Q10 quarters).

The estimated long-term multiplier indicates a 1.25% reduction in Return on Equity (ROE) and a 0.179% reduction in Return on Assets (ROA) as a consequence of the Business Intelligence (BI) system.

Initially, the observation of a negative long-term multiplier value may raise concerns as it suggests a decline in both profitability indicators, which contradicts the intended purpose of implementing the Business Intelligence (BI) system. The expectation behind implementing a BI system is to enhance the organization's analytical capabilities and, consequently, improve profitability. Therefore, further analysis and interpretation of the results are required to understand the underlying dynamics and potential reasons for this unexpected outcome.

An analysis of the dynamics of both Return on Equity (ROE) and Return on Assets (ROA) indicators from 2009 to 2020 reveals that while the implementation of the Business Intelligence (BI) system contributes to a decrease in their growth rates, it ultimately has a positive effect by slowing down the decline. Figure 1 illustrates the levels of ROE and ROA over the specified period.

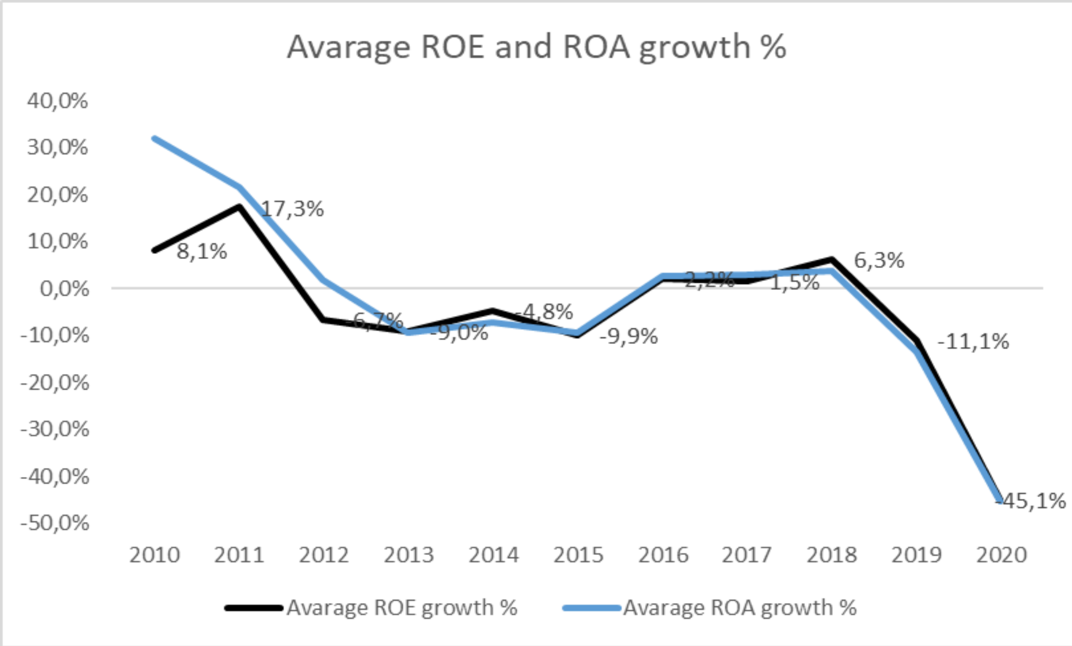



Source: Own elaboration.

**Figure 1: Average ROE and ROA Over 2009-2020 for 5 Selected Commercial Banks**

During the analyzed period, both the Return on Equity (ROE) and Return on Assets (ROA) ratios experienced a decline from year to year. The average level of ROE decreased from over 3 percentage points observed during the period of 2009-2014 to 2 percentage points in the subsequent years after 2015. Moreover, there was a further drop in ROE during 2019-2020. As a result, the average ROE for the five analyzed banks in 2020 was 1.3 percentage points.

The trend of decreasing profitability becomes even more apparent when examining the annual dynamics of ROE and ROA growth. Figure 2 presents the data depicting this trend.




Source: Own elaboration.

**Figure 2: Average ROA and ROA Growth % over 2010-2020 for 5 Selected Commercial Banks**

During the period of 2012-2018, the annual dynamics of the analyzed profitability indicators for the five selected commercial banks fluctuated between -10% and 10%. However, there was an exception during the initially successful period of 2010-2011, where the dynamics of both indicators exceeded the 20% threshold on an annual basis.

On the contrary, the average level of ROE and ROA dynamics experienced a significant decrease, reaching as low as -45% on an annualized basis during the final two years of the analyzed period, namely 2019-2020.

These observations highlight the varying dynamics and overall declining trend in profitability for the selected commercial banks during the specified period.

The analyzed levels of profitability indicators indeed indicate a general reduction in their values. However, the long-term multiplier obtained from Model (1) and Model (2), which suggests a decrease in the indicators' values in the long term due to the implementation of a Business Intelligence (BI) system, indicates that the implementation of BI can have a positive impact on profitability. This observation may seem contradictory considering the overall decline in ROE and ROA.

The explanation for this apparent contradiction lies in the fact that the implementation of BI slowed down the rate of decline. In other words, the decline in profitability ratios would have been even more significant without the implementation of BI, surpassing the values obtained for the long-term multiplier of the BI variable (1.25% and 0.0179%, respectively).

Therefore, although the profitability indicators decreased over time, the presence of the BI system mitigated the decline to some extent, suggesting a positive effect on profitability.

## 5. Discussion and Conclusions

Based on the findings, the main hypothesis (H0) stating that the use of a Business Intelligence (BI) management system between 2009 and 2020 improves the profitability of Polish commercial banks is supported. The analysis and results of the study provide evidence that the implementation of a BI system has a positive impact on profitability indicators in the context of Polish commercial banks.

The obtained models for both profitability ratios (ROE and ROA) showed statistical significance of the BI variable or its lags. Additionally, each model successfully passed the Sargan test and the second-order autocorrelation test, indicating that the instruments were appropriately chosen during estimation using the first-differences method. A summary of the results obtained is presented in Table 2.

**Table 2: Summary of Findings - Impact BI on ROE and ROA on Commercial Banks in Poland**

| Indicator name | Model no. | Statistical significance of the BI variable | Statistical significance of the model | Delay of BI impact in quarters | Impact of BI system | Long-term multiplier | Average growth of the YTY indicator from 2009 to 2020 |
|---|---|---|---|---|---|---|---|
| **ROE** | (1) | Yes | Yes | 0,1,2,3,8,9,10 | Yes | -1,25% | -3,7% |
| **ROA** | (2) | Yes | Yes | 0,1,2,3,8,9,10 | Yes | -0,0179% | -0,8% |

Source: Own elaboration.

In both models, the column "statistical significance of the BI variable" indicates that it was possible to obtain a model in which the BI variable or its lags were statistically significant at the 10% level or better. The column "statistical significance of the model" refers to the results of the Sargan test and the test for second-order autocorrelation and takes the value "Yes", in the cases analyzed both tests came out positive for each of the two models. It appears that the inclusion of the BI variable in the models had a significant influence on the profitability indicators, and the models themselves demonstrated statistical validity and reliability.

An interesting finding of the research is the determination of the time horizon at which the effects of the Business Intelligence (BI) system can be expected. This information is provided in the "delay of BI impact in quarters" column. The results indicate that the statistically significant delays associated with the BI variable were most commonly observed in the 1st and 3rd year after the implementation of the BI system. This implies that the effects of the BI system on profitability, as measured by ROE and ROA ratios, can be expected within approximately one year (0-9 months) and after three years (24 to 30 months) following its implementation. It is important to consider that this result indicates the time frame in which the Business Intelligence system begins to impact profitability. Understanding the specific time horizon at which the effects of the BI system become apparent can be valuable for organizations in assessing the effectiveness and return on investment of implementing such systems.

- The column "Impact of BI system" indicates whether an impact of the BI system has been identified based on the estimated model. It takes the value "yes" if the BI variable is statistically significant and the model passes the diagnostic tests successfully, with positive values for both ROE and ROA. This confirms the presence of a significant impact of the BI system on the profitability indicators. The column "long-term multiplier" provides information on how the level of the studied indicator is expected to change in the long term as a result of implementing the BI system. This value should be compared with the column "average growth of the year-over-year (YTY) indicator." The results obtained suggest that the implementation of Business Intelligence may contribute to slowing down the decline of both ROE and ROA, which aligns with the general trend observed in the commercial bank sector from 2009 to 2020.
- The study indicates a high probability of a positive impact of implementing the BI system on the profitability of commercial banks. The obtained results allow for a positive verification of the research hypothesis set in the introduction. However, the following limitations should be taken into account:
- The study was based on a limited number of cases (5 banks), and other banks were not included (the article describes the criteria for site selection). It is possible that the relationship between BI implementation and financial profitability may have a different direction and strength in those excluded banks.
- The profitability of a bank is influenced by various factors apart from BI implementation and general economic conditions, which were not isolated in this study.

- The method used to analyze the impact of BI implementation on bank profitability applies to the selected period of 2009-2020. Therefore, different results can be expected in other time periods, considering the advancement of business intelligence system technology and changes in external factors such as high inflation, high interest rates, pandemics, and armed conflicts in neighboring regions. Unambiguous and definitive verification of the indicated hypothesis, therefore, requires expanding the scope of the study, both in terms of the time horizon and the number of study subjects. In the future, the author plans to analyze organizations from other industries as well and take into account other factors that shape the impact of business intelligence systems on profitability indicators. These aspects will be the subject of further inquiries by the author.

Given the lack of research on the impact of BI systems on the profitability of Polish commercial banks after 2015, the following practical implications have been formulated and confirmed as still actual:

- The results of the study indicate that the implementation of Business Intelligence systems brings tangible benefits to the profitability of financial organizations, such as commercial banks.
- The research implications of this study may suggest to top management that implementing business intelligence systems can benefit the organization.

## References

Al-Homaidi, E. A., et al (2020) "Internal and external determinants of listed commercial banks' profitability in India: dynamic GMM approach.", *International Journal of Monetary Economics and Finance*, *13*(1), pp. 34-67, DOI: https://dx.doi.org/10.1504/IJMEF.2020.10025082

Almaqtari, et al (2019) "The determinants of profitability of Indian commercial banks: A panel data approach", *International Journal of Finance & Economics*, *24*(1), pp. 168-185, DOI: https://doi.org/10.1002/ijfe.1655

Anderson, T.W., Hsiao C. (1981) "Estimation of Dynamic models with Error Components", *Journal of the American Statistical Association*, 76, pp. 598-606.

Anderson T.W., Hsiao C. (1982) "Formulation and estimation of dynamic models using panel data", *Journal of Econometrics*, 18, pp. 47-82.

Arellano, M., Bond, S. (1991) "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", *The Review of Economic Studies*, 58(2), pp. 277-297.

Coleman, N., Feler, L. (2015) "Bank ownership, lending, and local economic performance during the 2008–2009 financial crisis.", *Journal of Monetary Economics*, 71, pp. 50-66.

Dańska-Borsiak B. (2009) "Zastosowania panelowych modeli dynamicznych w badaniach mikroekonomicznych i makroekonomicznych", *Przegląd Statystyczny*, 56(2), pp. 25-41.

Hussinki, H. (2022) "Business Analytics and Firm Performance: A Literature Review." *In European Conference on Knowledge Management*, Vol. 23, No. 1, pp. 527-532, DOI: https://doi.org/10.34190/eckm.23.1.560

Hsiao, C. (2003) *Analysis of Panel Data 2nd edn,* Cambridge University Press, Cambridge., pp. 69-111.

Jaworski, J., Czerwonka, L. (2022) *Struktura kapitału przedsiębiorstw w Polsce*., CeDeWu, Warszawa, pp. 161-167.

Lachenmaier S., Rottmann H. (2011) "Effects of innovation on employment: A dynamic panel analysis.*", International Journal of Industrial Organization*, 29(2), pp. 210-220.

Mileva E. (2007) "Using Arellano-Bond dynamic panel GMM estimators in Stata*", Economics Department*, Fordham University, pp. 1-10.

Osińska, M., Kośko, M., Stempińska, J. (2007) *Ekonometria współczesna*, Dom Organizatora, Toruń, pp. 409-421.

Ossowski J. C. (2007) "Wstąpienie Polski do Unii Europejskiej*", Czasopismo Naukowe Sopockiej Szkoły Wyższej*, 83, pp. 6-7.

Raymond W., et al. (2015) "Dynamic models of R & D, innovation and productivity: Panel data evidence for Dutch and French manufacturing.", *European Economic Review*, 78, pp. 285-306.

Tunowski, R. (2019) *Wpływ Wykorzystania Systemów Business Intelligence Na Kondycję Finansową Banków komercyjnych W Polsce* [*The Impact Of The Use Of Business Intelligence Systems On Financial Condition Of Commercial Banks In Poland*], CeDeWu: Warsaw, Poland, pp. 15-69, pp. 87-92.

Tunowski, R. (2020) "Sustainability of Commercial Banks Supported by Business Intelligence System", *Sustainability*, 12, 4754., DOI: doi:10.3390/su12114754.

Tunowski, R. (2022) "Measure The Benefits of Implementing a Business Intelligence System.", Proceedings of the 40th International Business Information Management Association Conference, pp. 1129-1132.