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MULTI-CRITERIA ANALYSIS OF THE BALTIC BANKS FROM CLIENT ATTRACTION AND PROFIT GENERATION PERSPECTIVES

Karolina KRIŠČIUKAITYTĖ [1], Tomas BALEŽENTIS [2✉], Dalia ŠTREIMIKIENĖ [2]

[1]*Faculty of Economics and Business Administration, Vilnius University, Vilnius, Lithuania*
[2]*Vilnius Gediminas Technical University, Vilnius, Lithuania*

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Abstract. The economic and regulatory environment banks operate in poses challenges in regard to different facets of sustainability and requires proper managerial and technological innovations. Bank performance can be analysed from various viewpoints. Therefore, it is important to develop comprehensive frameworks for assessment of banking performance. The paper develops a two-stage approach for measuring banking performance from the client attraction and profit generation perspectives. The multi-criteria framework involving three multi-criteria decision-making methods is developed to ensure robustness of the results. The empirical research deals with the 17 commercial banks operating in the three Baltic States. This case is interesting as it covers a low-interest-rate environment. While Lithuanian banks excelled in the client attraction perspective, the results for 2017–2021 suggest that they should focus on the improvement of performance in this regard and profit generation if compared to banks operating in Latvia and Estonia.

Keywords: bank performance, profitability, client attraction, multi-criteria analysis, composite indicator, hybrid approach.

JEL Classification: G21, G39.

✉Corresponding author. E-mail: *t.balezentis@gmail.com*

1. Introduction

Banks play an important role in the economies of all countries, contributing to multiple kinds of prosperity. The banking system accumulates financial resources and manages risk thereby serving as a primary provider of financial capital for a national economy (Drigă & Dura, 2014). In addition, the quality of life is indispensable from economic growth (Zhu & Guo, 2024). Against this backdrop, the role of the banking system becomes crucial as it allows for increasing the efficiency of the whole economy. Thus, the efficiency of the banking system is an important determinant of sustainable growth.

Banking systems face different challenges across the regions (Barth et al., 2003; Mateev et al., 2024). The Baltic States reward further analysis as the banking system there has seen serious transformations and feature dependence on the major foreign banks. The national economies of the Baltic States have been emerging for the last four decreased with serious shocks coming from the lack of regulation in the initial development stages, economic crises, and further consolidation. Recently, the emergence of internet banking and digitalization has allowed for greater competition in the traditional banking sector. The period of (near) zero interest rate has also urged banks operating in the Baltic States with relatively low population size to opt for novel pricing options. In this context, the attractiveness of different banks has changed. Also, the sector has seen a number of mergers and acquisitions besides closures. This context implies a need for analysis of the dynamics in the relative performance of the banks.

The performance of banks can be analyzed by taking one of the commonly used approaches viz., the intermediation or production approach. The intermediation approach focuses on the consumer needs and treats the abilities of the banks to transform deposits into loans. As for the production approach, it considers deposits and loans as two outputs resulting from the banking operations defined by the operational expenses. In this case, the needs of consumers are less important as the profits generated by non-loan activities may be sufficient to consider banking activity as profitable. The dichotomy in the bank assessment approaches calls for further analysis of the relative bank performance. In this study, we discuss different indicator systems reflecting banking performance with regard to client attraction and profit generation. Therefore, the paper contributes to the existing literature by offering multi-criteria approaches based on different viewpoints towards operation and performance of a bank system.

The paper aims to assess the relative performance of banks operating in the Baltic States using multiple criteria analysis over 2012–2021 by taking the client attraction and profit generation perspectives. The proposed framework allows to assess different aspects of banking performance which is interesting amid the changes in the context the Baltic States' banks operate in. The features of the Baltic States banking market include (1) small market size, (2) excessive liquidity in the banking system, and (3) low interest rate environment for the long period.

As the banking activities are diverse, multi-criteria evaluation is suitable (and required) to gauge the relative performance of the banks operating in the Baltic States. Multi-criteria approaches can be used in diverse areas (Streimikis, 2025). In this study, we resort to the SAW, TOPSIS and EDAS methods. Then, the indicator systems that enable comprehensive assessment of client attraction and profit generation by banks are developed. The panel data for 2012–2021 are used. The main 17 Baltic banks are covered. These include seven observations from Estonia, five from Latvia and five from Lithuania. Fourteen indicators were considered to construct the two indicator sets.

The paper is structured as follows: Section 2 reviews the literature on multi-criteria analysis of the bank performance. Section 3 describes the methods, indicators, and data sources used in empirical research. Section 4 presents and discusses the results. Section 5 presents a sensitivity analysis. The final section summarizes and concludes the article.

2. Literature review

The banking sector has seen an increased concern over sustainability (Da Silva Inácio & Delai, 2022; Saadaoui & Ben Salah, 2023; Abueid et al., 2023). The stakeholders involved in the banking activities are diverse (clients, regulators, bankers etc.). Therefore, assessment of banking sustainability requires combining multiple (conflicting) objectives. Thus, use of the MCDM techniques for assessment of the measures of different aspects of banking sustainability have become prevalent in the literature (Ecer et al., 2024).

Beheshtinia and Omidi (2017) proposed a framework for assessing performance of banking with focus on sustainability. The proposed approach involves several MCDM methods

(AHP, TOPSIS, VIKOR). The extensions of the aforementioned MCDM methods were used by incorporating fuzzy sets and modified digital logics. As regards identification criteria, the balanced scorecard approach and corporate social responsibility theory were used.

Wu et al. (2009) utilized the fuzzy AHP, SAW, TOPSIS, and VIKOR to appraise banking performance. The 23 indicators were aggregated to construct a comprehensive one. The balanced scorecard approach also appeared in further studies based on the MCDM. Shaverdi et al. (2011) applied the balanced scorecard approach for creation of the indicator system that allows one to compare the performance of the private banks. The fuzzy logic was used to operationalize the selected MCDM approaches (TOPSIS, VIKOR, and ELECTRE).

Wanke et al. (2016a) relied on the CAMELS approach to derive the criteria for analysis of the bank performance. The fuzzy AHP was used to obtain the weights of the criteria and the TOPSIS method was applied to aggregate the data. The final step involved the use of artificial neural networks to identify the impact of the determinants of the bank performance (Wanke et al., 2016b). Gupta et al. (2020) developed a framework comprising 10 indicators to assess bank performance in a comprehensive manner. The interval valued fuzzy numbers were used to facilitate the TOPSIS approach. The weights of the criteria were derived by using the AHP technique. Raut et al. (2017) integrated fuzzy AHP and TOPSIS approaches to assess the sustainability of banks. The balance scorecard approach was utilized when constructing the indicator set.

Sama et al. (2022) relied on the CRITIC approach for determining the weights of criteria of banking performance. Then, the TOPSIS and grey relational analysis were used for aggregation of multiple criteria. The rankings of banks differed depending on the methods applied. Roy and Shaw (2023) developed an indicator system for measurement of the performance of mobile banking systems. The fuzzy BWM was applied to elicit the weights of criteria. Then, the TOPSIS method was used to obtain comprehensive evaluation scores. Zhao et al. (2019) discussed the assessment of sustainability of banks and used six groups of criteria. The DEMATEL and VIKOR methods were used for the analysis.

Dinçer and Yüksel (2018) presented a framework for analyzing the performance of deposit banks. The data came from expert assessment and content analysis. The fuzzy AHP, ANP, and VIKOR techniques were applied. The balanced scorecard approach was used to construct the indicator system. Wanke et al. (2023) used the sign decomposition approach for multi-criteria analysis of bank performance. The artificial neural networks were used to predict the bank performance scores. Ünlü et al. (2022) developed an approach for assessing bank performance based on financial ratios. The weights of the multiple criteria were obtained via the SWARA II and MEREC methods. The MARCOS method was used to aggregate the data and obtain the utility scores.

The literature review suggests that there are several major strands prevailing in the sense of the choice of the criteria for banking performance (e.g., balanced scorecard, CAMELS). The use of imprecise information induced the need for fuzzy approaches. The studies on banking performance used several MCDM methods to ensure robustness of the results. Furthermore, the earlier literature looked at the performance of the banks from different perspectives, yet no study attempted to assess the performance of banks from multiple perspectives by using the MCDM.

The approaches relying on pair-wise comparisons (e.g., AHP, BWM) may provide flexible judgements in regard to the criteria importance perceived by the stakeholders. However, this requires dedicated expert efforts and relatively complicated software. The approaches involving reference point or value function are in this case preferred to establish a framework that would be easily replicable with new data. Furthermore, we seek to ensure the robustness of the analysis from the aggregation viewpoint. Thus, we seek to combine different approaches relying on the reference point and value measurement (Belton & Stewart, 2002).

3. Methods and data

3.1. Methods

There are various Multicriteria Evaluation Decision-Making (MCDM) methods available that can be applied for assessment of the banks' performance with regard to multiple objectives. Using different MCDM approaches can help to ensure robustness of the results. Accordingly, this study uses the three MCDM) methods – Simple Additive Weighting (SAW), Technique for Order of Preference by Similarity to an Ideal Solution (TOPSIS) and Evaluation based on Distance from Average Solution (EDAS) – that differ in the sense of the construction of the 'benchmarks' used for constructing the utility scores. These differences appear due to the underlying normalization techniques and aggregation principles.

The SAW approach relies on the linear normalization where only optimal values (maximal values for benefit criteria) are used as a reference. Thus, the resulting utility scores can be considered as those defined with respect to the hypothetical optimal point. The EDAS approach relies on the distances from the sample average. Indeed, the normalized values are based on the distances scaled by the average point. The TOPSIS approach involves vector normalization where the whole sample is considered. Also, the aggregation proceeds by defining the positive and negative ideal points. In this regard, the whole sample is considered when constructing the references for utility scores. Table 1 summarizes these points.

Table 1. Methodological assumptions applied when constructing reference values for selected MCDM approaches

MCDM approach	Optimal value	Average	Worst value
SAW	+		
TOPSIS	+	+	+
EDAS		+	

The *SAW* approach involves an additive utility function with linear weights attached to the criteria. The additive utility function is used by, e.g., Chakraborty and Zavadskas (2014). The data for SAW are normalized by using the max linear normalization. Various procedures are applied to process the benefit criteria that cannot be normalized in the same manner as the benefit ones. In order to take into account, the different nature of the two types of criteria, we use the min-max linear normalization (Vafaei et al., 2016):

$$x_{ij}^{*} = \begin{cases} \dfrac{x_{ij} - \min\limits_{i} x_{ij}}{\max\limits_{i} x_{ij} - \min\limits_{i} x_{ij}}, j \in B, \\ \dfrac{\max\limits_{i} x_{ij} - x_{ij}}{\max\limits_{i} x_{ij} - \min\limits_{i} x_{ij}}, j \in C, \end{cases} \quad (1)$$

where x_{ij} is the value of the j-th criterion for the i-th alternative (a bank), x_{ij}^{*} is the normalized value, B and C are the sets of the benefit and cost criteria respectively. The SAW is then applied by defining the additive utility function as follows:

$$y_i^{SAW} = \sum_{j=1}^{n} w_j x_{ij}^*, \tag{2}$$

where y_i^{SAW} is the utility score for the i-th alternative and w_j is the weight for the j-th criterion such that $\sum w_j = 1$. Higher value of the utility score indicates better performance.

The *TOPSIS* approach (Hwang & Yoon, 1981) was developed to rank alternatives with regard to the two ideal solutions that are, indeed, hypothetical ones. These ideal solutions are based on the normalized values obtained through the vector normalization:

$$x_{ij}^* = \frac{x_{ij}}{\left(\sum_{i=1}^{m} x_{ij}^2\right)^{1/2}}. \tag{3}$$

Then, the ideal solutions are defined as the following vectors:

$$\begin{aligned} x^+ &= \left\{\max_i x_{ij}, j \in B; \min_i x_{ij}, j \in C\right\}; \\ x^- &= \left\{\min_i x_{ij}, j \in B; \max_i x_{ij}, j \in C\right\}. \end{aligned} \tag{4}$$

The Euclidean distances to the ideal solutions are calculated for each observation:

$$\begin{aligned} d_i^+ &= \left(\sum_{j=1}^{n} \left(x_{ij} - x_j^+\right)^2\right)^{1/2}; \\ d_i^- &= \left(\sum_{j=1}^{n} \left(x_{ij} - x_j^-\right)^2\right)^{1/2}. \end{aligned} \tag{5}$$

The utility score is calculated as the relative distance to the negative ideal alternative:

$$y_i^{TOPSIS} = \frac{d_i^-}{d_i^- + d_i^+}. \tag{6}$$

The higher value of the utility score implies better performance of an alternative.

The *EDAS* approach (Keshavarz Ghorabaee et al., 2015) relies on the calculations of the positions of the alternatives with respect to the sample average. The average is defined as:

$$\bar{x}_j = \frac{1}{m} \sum_{i=1}^{m} x_{ij}. \tag{7}$$

The positive distances are then obtained as:

$$\begin{aligned} d_{ij}^+ &= \frac{\max\left\{0, x_{ij} - \bar{x}_j\right\}}{\bar{x}_j}, j \in B; \\ d_{ij}^+ &= \frac{\max\left\{0, \bar{x}_j - x_{ij}\right\}}{\bar{x}_j}, j \in C. \end{aligned} \tag{8}$$

Similarly, the negative distances are obtained in the following manner:

$$
\begin{aligned}
d_{ij}^{+} &= \frac{\max\left\{0, \bar{x}_j - x_{ij}\right\}}{\bar{x}_j}, j \in B; \\
d_{ij}^{+} &= \frac{\max\left\{0, x_{ij} - \bar{x}_j\right\}}{\bar{x}_j}, j \in C.
\end{aligned} \tag{9}
$$

The weights are then applied to the distances obtained in Eqs. (8)–(9) to derive the aggregate indicators of performance with reference to the positive and negative deviations from the sample mean:

$$
\begin{aligned}
d_i^{+} &= \sum_{j=1}^{n} w_j d_{ij}^{+}; \\
d_i^{-} &= \sum_{j=1}^{n} w_j d_{ij}^{-}.
\end{aligned} \tag{10}
$$

The normalized distances are defined as:

$$
\begin{aligned}
\hat{d}_i^{+} &= d_i^{+} \Big/ \max_i d_i^{+}; \\
\hat{d}_i^{-} &= 1 - d_i^{-} \Big/ \max_i d_i^{-}.
\end{aligned} \tag{11}
$$

Finally, the utility score is calculated as the average of the normalized aggregate distances:

$$
y_i^{EDAS} = \frac{1}{2}\left(\hat{d}_i^{+} + \hat{d}_i^{-}\right). \tag{12}
$$

The higher value of the utility score indicates better performance.

The ranking of banks can be derived from the order of utilities scores. However, ranks of the banks may differ across the MCDM approaches. Therefore, utility scores rendered by the three approaches can be further combined in order to derive a more robust measure of utility. The min-max linear normalization is applied on the utility scores in Eqs. (2), (6), and (12):

$$
\hat{y}_i^{\xi} = \frac{y_i^{\xi} - \min_i y_i^{\xi}}{\max_i y_i^{\xi} - \min_i y_i^{\xi}}, \quad \xi = \left\{SAW, TOPSIS, EDAS\right\}. \tag{13}
$$

The normalization in Eq. (13) is invoked in order to ensure that the same interpretation of the utility scores rendered by different methods is maintained. Specifically, the linear normalization in Eq. (13) suggests that the utility scores can be interpreted as a percentage of observations dominated by a certain observation (bank-year). The *composite utility score* is then calculated as simple average:

$$
y_i = \frac{1}{3} \sum_{\xi = \left\{SAW, TOPSIS, EDAS\right\}} \hat{y}_i^{\xi}. \tag{14}
$$

The higher value of the average utility score indicates better performance. Note that we use the weight of 1/3 as a baseline and also try other values to check robustness of the results.

3.2. Indicators of bank performance

In this sub-section, we discuss the criteria describing bank performance. Compared to earlier studies, we further group the criteria into those representing attraction of the funds (clients) and those describing the economic productivity (generation of profit). The literature review and consideration of situation of the banking sector in the Baltic States allowed to identify the relevant indicators. As a result, fourteen indicators describing efficiency were selected for multi-criteria analysis of banking activity. Data that are available from annual reports or other public sources were considered.

As it was mentioned before, banks are evaluated from the two perspectives: clients and shareholders. In general, the intermediation approach can be used to describe and combine these two perspectives (Figure 1). According to intermediation approach (Henriques et al., 2020), a bank acts like a financial intermediary by attracting deposits and using them as an input for profit generation. Then, interest and non-interest revenue (income) are generated as a result of financial intermediation. This study decomposes the overall intermediation process into two stages related to client attraction and profit generation that is based on the funds attracted.

Therefore, two sets of indicators are used in order to construct composite indicators describing banking activities. The first set of indicators evaluates the bank ability to attract clients. Generally, this is important for attracting deposits as the main input needed for revenue generation. Indicators for this set are chosen from the deposit holder's (client) perspective: the indicators that are likely to improve bank attractiveness from the viewpoint of (potential) customers are considered. The second set of indicators evaluates the revenue generation and gives emphasis on bank profitability. Indicators for this set are chosen from the bank's shareholder perspective that would otherwise would not be interesting for the customers.

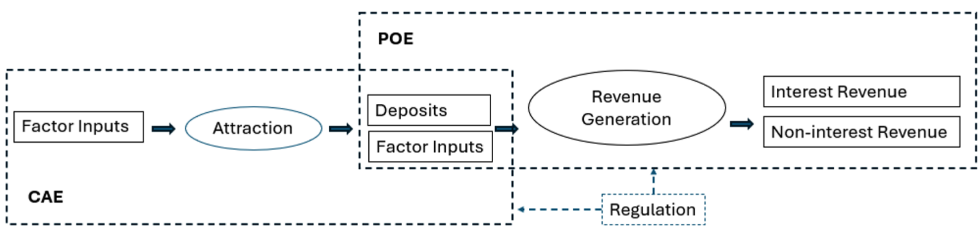

Figure 1. Client attraction efficiency (CAE) and profit-oriented efficiency (POE) (source: designed by the authors)

The use of the multi-criteria assessment requires determining whether a certain indicator is maximized or minimized to approach the optimum point. The set of indicators along with weights and directions of optimization are presented in Table 2. It is assumed that the importance of the criteria within each set is equal. The chosen sets comprise ten indicators each. Note that some indicators have zero weights for a certain set which means that they are relevant for a single set only.

For the CAE side the principle followed in designing the criteria set (and weights) was that trust in bank, higher interest received, and sustainability-related indicators were considered. As for POE, the performance indicators were considered alongside the ability to utilize the assets freely. Consequently, the directions of optimization may vary across the sets. Four indicators – Total capital adequacy ratio, Cash and cash balances with central banks to deposits, Net interest income to Assets, and Net interest income to Loans – show such differences. The criteria chosen for the analysis are discussed in detail below, along with a review of the relevant literature.

Table 2. Criterion weights and directions for optimization

Indicator	Client attraction efficiency (CAE)		Profit oriented efficiency (POE)	
	Weight	Direction	Weight	Direction
Total capital adequacy ratio, %	0.1	max	0.1	min
Return on Assets, %	0.1	max	0.1	max
Return on Equity, %	0	max	0.1	max
Net profit per employee, EUR thousands	0	max	0.1	max
Cost-to-Income, %	0	min	0.1	min
Deposits to Assets, %	0.1	max	0.1	max
Cash and Cash balances with central banks to Deposits, %	0.1	max	0.1	min
Loans to Assets, %	0.1	max	0	max
Assets per employee, EUR thousands	0	max	0.1	max
Inversed HHI on Income (Diversification of revenue)	0.1	max	0.1	max
Net interest income to Assets	0.1	min	0.1	max
Net interest income to Loans	0.1	min	0	max
Number of sustainability related disclosures, sentences/annual report	0.1	max	0	max
Interest paid to Deposits, %	0.1	max	0	max
Total	1		1	

Total Capital Adequacy Ratio (TCAR) represents the ratio of a bank's eligible capital to its risk. Banking sector is heavily regulated sector and one of the areas of regulation is to ensure stability of the overall banking sector by setting requirements for its capital. Khan et al. (2020) notice that TCAR shows the ability of a bank to face abnormal losses, its strength and stability. TCAR is the most general risk assessment indicator, and its minimum value is set in regulatory requirements. When measuring the efficiency of banks, earlier literature used "Total capital adequacy ratio" indicator, see Baselga-Pascual et al. (2018), Kolari et al. (2019), Paule-Vianez et al. (2019), Gambetta et al. (2019), Shen et al. (2016), Izzeldin et al. (2020), San-Jose et al. (2018), Buallay et al. (2021), Yılmaz and Nuri Ine (2018). The higher TCAR, the more bank's capital is located to liquid assets, the less bank's capital can be used in more profitable but riskier projects. Therefore, the higher TCAR is positive factor for clients as the higher TCAR, the more stable bank, the better bank can meet obligations to deposit holders, i.e. paying out the clients' deposits. For shareholders, TCAR shows the regulatory constrain on the allocation of capital in order to manage risk, the lower, i.e., keeping the necessary minimum, TCAR indicates that the bank chooses the riskier projects, and its profitability can be higher. We acknowledge that there are more nuances for risk taking: the bank not meeting

TCAR requirements can face the penalties or loose banking licence; the tolerance for more risk should go hand in hand with ability to manage the risk. But this aspect is let out from the scope of this research.

Return on Assets (ROA) is the ratio of net profit to total assets and is one of the key indicators used in research to assess the efficiency and profitability of banks (Buallay, 2019; Buallay et al. 2021; Valls et al. 2020; Baselga-Pascual et al., 2018; Tunowski, 2020; Niţescu & Cristea, 2020; Stoica et al., 2020; Karkowska, 2020; Gutiérrez-López et al., 2020; Tan & Tsionas, 2020; Khan et al., 2020; Manta et al., 2020; Mansour & El Moussawi, 2020; Forcadell et al., 2019; Vo, 2018). The indicator describes the efficiency of the use of the bank's assets. The higher the value of the indicator, the more profitable use of bank assets. It is primarily an indicator of managerial efficiency (Baselga-Pascual et al., 2018). ROA is the main indicator for analyzing the profitability of banks, mainly due to their financial intermediation role: the deposits are the most important source of assets for bank's lending activities. The higher ROA the better for shareholders and clients, as the profitable bank is economically stable bank and can absorb the negative economic events.

Return on Equity (ROE) is the ratio of net profit and total equity and is the main indicator used by shareholders to measure the ability of company, not only banks, to generate profit for the one euro invested by shareholders. The ROE is no less important than the ROA in analysis (Tunowski, 2020; Karkowska, 2020; Valls et al., 2020; Gemar et al., 2019; Gutiérrez-López et al., 2020; Tan & Tsionas, 2020; Manta et al., 2020; Platonova et al., 2018, Shen et al., 2016; Scholtens & van't Klooster, 2019; Sharif et al., 2019; Balci & Ayvaz, 2020). However, ROE neglects the higher risk associated with high leverage and the impact of regulations on leverage (Platonova et al., 2018).

Net profit per employee, EUR thousand per employee, is the ratio of net profit to average number of bank's employees. It is another indicator to evaluate profitability per input as the equity, assets and employee are the main inputs in the bank efficiency.

Cost-to-Income (C/I) is the ratio of the operating expenses and the operating income, the less indicator the more efficient is bank. Cost-to-income is also common indicator used for determining the efficiency of a bank (Baselga-Pascual et al., 2018; Tunowski, 2020; Gutiérrez-López et al., 2020; Korzeb & Samaniego-Medina, 2019; Manta et al., 2020). The indicator can be improved not only by increasing income, but also by reducing costs at all levels of output (Khan et al., 2020). For shareholders it is important whether costs are managed, controlled well.

Deposits to Assets (D/A) is the ratio of total deposits to total assets and it shows what part of bank's assets is funded by deposits. Deposits are the cheaper source to fund bank's activities, if compared to equity. Also, it is considered to be the most stable source of assets. Therefore, from the POE point of view the higher D/A the higher profitability. From CAE point of view, bank's ability to attract deposits shows the trust of clients, the higher D/A the more trustworthy is the bank for the clients. This trust is usually built via long period. The new bank can attract deposits via good marketing strategy, good communication of bank's vision. Only few authors used this indictor (Balci & Ayvaz, 2020), others preferred to take Total deposits.

Cash and Cash balances with central banks to Deposits is indicator that shows how the bank uses the obtain funds. By keeping cash and cash balances with central banks the bank minimises the counterparty risk, however this is also an indicator that bank does not have suitable alternative where to use the funds, i.e. funds are not used in loans, in investing. This indicator is partially defined by legal capital adequacy requirements, overall market conditions and ability of bank to find profitable projects, loans to invest. The lower this indicator the better bank ability efficiently use its assets. Although this indicator is not used in reviewed literature, we argue for its inclusion in multicriteria optimization. From the client perspective, the more bank has cash (liquid assets), the more bank is able to absorb negative events.

Loans to Assets (L/A) is the ratio of total loans to total assets and represents the share of assets that is allocated for lending, traditional output in banking sector, and as result the more revenues will be from interest-earning assets (Abbas et al., 2021). The more clients want to borrow, the better-quality projects bank can choose from. The better quality of loans the less risky is bank. This indicator was chosen for CAE, but not for POE set as bank can allocate its assets not only for loans but for other revenue generating investments.

Assets per employee, EUR thousand per employee, is the ratio of total assets and average number of bank's employees. From profit-oriented efficiency perspective, the more assets can one employee manage, the better efficiency of bank is.

Inverse Herfindahl-Hirschman Index (*IHHI*) *on Income* shows the diversification of revenues from different type of income of banking activities: net interest, net fee and commissions, net financial, and other operating income. Baselga-Pascual et al. (2018) find that higher income diversification favors bank profitability. IHHI on Income varies from 0 to 0.75, where 0 indicates no diversification, 0.75 indicates that bank's income is equally distributed across four banking activity areas:

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$$IHHI = 1 - \left(\frac{\text{Net Interest Income}}{\text{Total Income}}\right)^2 - \left(\frac{\text{Net Commission Income}}{\text{Total Income}}\right)^2 - \left(\frac{\text{Net Financial Income}}{\text{Total Income}}\right)^2 - \left(\frac{\text{Other Income}}{\text{Total Income}}\right)^2, \quad (15)$$

where Total income is the sum of absolute values of net interest, net commission, net financial and other income.

Net interest income to Assets has different directions in this study. Bank's assets comprise from deposits and shareholder equity, i.e. they are inputs for producing loans and investment. The less are interest costs for deposits, the more are interest margin for loans, the higher profit-oriented efficiency is achieved (Özçalıcı et al., 2022). Contrary, for the client's the less this indicator the better as it might mean that the bank pays the higher interest rates for deposits and sets the lower margins for loans.

Net interest income to Loans also reflects the less margin between the loans and deposits; the lower indicator the more attractive conditions to borrow are for clients (Bhaskaran et al., 2023).

Number of sustainability related disclosures that are found in the reports of the bank is proxy measure to reflect the perception that clients might have form from the overall communication about the bank. A similar indicator is introduced by Stauropoulou and Sardianou (2019). For this study, phrases that contain selected words (sustainable, ESG, green, environmental, vision, clients, customer, SME, SSE, stable, digital, innovati*, entrepreneurship, ethical, responsible) are taken into account. The more disclosure bank makes on its vision, dealings with clients, policy with dealings with small and medium enterprises, entrepreneurship, bank views to stability, sustainability, innovation, the more transparent it is for a client. Reasonable transparency brings the trust between bank and client.

Interest paid to Deposits can be used as proxy for interest rates of deposits (Bakashbayev et al., 2020). The more interest is paid for deposits, the more competitive bank is for deposits attraction. The impact of this indicator depends on interest rates for deposits in other banks. In this study "interest paid" was taken either from profit (loss) statements or from cash flows statements.

Another important indicator that was not used for the multicriteria calculations is the bank size. Usually, it can be shown either by Number of full-time employees or the Total assets or its natural logarithmic value (Baselga-Pascual et al., 2018; Tan & Tsionas, 2020; Manta et al., 2020; Platonova et al., 2018, Vo, 2018; Scholtens & van't Klooster, 2019; Mansour & El Moussawi, 2020; Vunjak et al., 2020; Shen et al., 2016). This variable can be important if one assumes that the bigger a bank, the less exposed it is to existing credit risk and the more adequate their impaired loan provisions will be (Gemar et al., 2019). However, bank efficiency does not always depend on its size, and we resort to relative indicators in this study.

3.3. Data

Data for indicators was collected from financial reporting of the Baltic banks. The range of data was taken from 2012 till 2021. The banks that were selected had a substantial market share and were active during the period analyzed. The Baltic region is represented by seven banks from Estonia and five banks from Latvia and Lithuania. In total, 156 bank-year observations were collected (the unbalanced panel covers 17 banks and 10 time periods which makes 9.17 observations per bank on average). With the Baltic states joining the eurozone, the financial data was converted from the local currency to the euro at fixed exchange rates.

A 95% winsorisation was performed to eliminate extreme values of all indicators. The winsorization allows one to mitigate the effects of potential outliers (e.g., negative values in ROE, ROA) that may have been observed due to occasional shocks. Table 3 summarizes the characteristics of transformed by winsorisation data.

Table 3. Summary statistics for winsorized data (N = 156)

Indicator	Mean	Median	Standard Deviation	Min	Max	Coefficient of variation
Total capital adequacy ratio, %	21.98	20.60	6.85	10.96	40.68	0.31
Return on Assets, %	1.45	1.23	0.93	0.08	4.09	0.64
Return on Equity, %	11.58	11.23	5.90	0.80	26.52	0.51
Net profit per employee, EUR thousands	43.07	40.64	27.56	1.23	98.58	0.64
Cost-to-Income, %	52.59	49.56	13.95	33.80	84.60	0.27
Deposits to Assets, %	77.39	79.86	9.95	52.13	89.58	0.13

End of Table 3

Indicator	Mean	Median	Standard Deviation	Min	Max	Coefficient of variation
Cash and Cash balances with central banks to Deposits, %	24.03	23.07	12.62	4.58	55.19	0.53
Loans to Assets, %	59.04	61.30	17.14	10.44	84.72	0.29
Assets per employee, EUR thousands	3,330.56	3,181.34	1,827.94	474.94	8,270.04	0.55
Inversed HHI on Income (Diversification of revenue)	0.52	0.57	0.14	0.15	0.67	0.26
Net interest income to Assets	0.03	0.02	0.03	0.01	0.15	1.03
Net interest income to Loans	0.05	0.04	0.04	0.02	0.19	0.78
Number of sustainability related disclosures, sentence/ annual report	51.65	41.00	32.97	10.93	164.88	0.64
Interest paid to Deposits, %	0.91	0.64	0.78	0.10	3.56	0.86

4. Results and discussion

Several major changes in the economic environment were faced during the 2012–2021 period. First, three Baltic countries joined the eurozone by adopting the euro at the beginning of the corresponding year: Estonia in 2011, Latvia in 2014, Lithuania in 2015. Before then, local Baltic currencies were pegged to the euro. Secondly, this period corresponds with a low-interest rate environment. The European Central Bank introduced its negative interest rate policy in June 2014 when its deposit facility rate was cut below 0%, to –0.1% (Claeys, 2021). The negative rates fully transmitted to the whole yield curve. The 6-month Euribor, which serves as the base interest rate for corporate and mortgage lending in the Baltics, entered the negative territory between late 2015 and early 2022[1]. The third factor that banks faced is excess liquidity in the system from 2015 till 2022 due to the central banks policies on quantitate easing in order to manage the financial crisis and the COVID-19 crisis[2].

Claeys (2021) states that negative rates encourage investors to seek higher returns by acquiring riskier assets, and banks tend to purchase various assets in order to shift negative-yielding reserves to other banks. When banks hold reserves above the minimum required by the central bank, they face direct costs in the form of negative rates. The banking sector cannot avoid this cost as it is flooded with liquidity. A potential decline in the net interest income of banks can be observed, as banks do not make the deposit rates below 0% for households or corporations in fear that they move their accounts to another bank to avoid negative rates. On the other hand, costs of negative rates can be passed to loans takers by increasing lending margins.

1 https://www.euribor-rates.eu/en/current-euribor-rates/3/euribor-rate-6-months/.

2 https://www.ecb.europa.eu/press/key/date/2023/html/ecb.sp231109~fd9153a89f.en.html

Though the Baltic banking sector assets grew several times in 2012–2021, the banking sector overall managed to maintain the activities – deposit attraction, lending, cost, risk management – as usual. The Baltic banking sector demonstrated a relatively stable performance in such indicators as Deposit-to-Assets, Cost-to-Income, TCAR, Loans-to-assets, and inversed HHI on Income (Table 3). However, a high variation was detected in the indicators that are related to the net interest income, i.e., Net interest income to assets, Net interest income to Loans, Interest paid to Deposits. The utility scores calculated using the client attraction perception and the profit-oriented perception are presented in Table 4.

Table 4. Averages of CAE and POE utility values by bank and country in 2012–2022

Bank	Average of CAE Utility				Average of POE Utility			
	Average	SAW	TOPSIS	EDAS	Average	SAW	TOPSIS	EDAS
EE_1	0.2339	0.2290	0.2268	0.2460	0.8254	0.6560	0.9134	0.9066
EE_2	0.6646	0.6843	0.6864	0.6231	0.4228	0.4349	0.3755	0.4579
EE_3	0.6388	0.6587	0.6535	0.6043	0.4711	0.4648	0.4325	0.5158
EE_4	0.6768	0.7582	0.6583	0.6140	0.5471	0.5635	0.4775	0.6003
EE_5	0.2677	0.2700	0.3432	0.1899	0.4848	0.5687	0.3685	0.5171
EE_6	0.4923	0.4723	0.5621	0.4424	0.2427	0.2441	0.1840	0.2998
EE_7	0.6487	0.6476	0.6824	0.6161	0.4703	0.5138	0.3796	0.5176
LT_1	0.5743	0.5689	0.6277	0.5262	0.3599	0.3314	0.3311	0.4173
LT_2	0.4409	0.4509	0.5134	0.3585	0.3255	0.3772	0.2534	0.3458
LT_3	0.5838	0.5856	0.6247	0.5410	0.3169	0.3294	0.2719	0.3493
LT_4	0.4610	0.5282	0.5058	0.3491	0.2096	0.2598	0.1722	0.1967
LT_5	0.7518	0.8298	0.7269	0.6986	0.4141	0.4759	0.3160	0.4505
LV_1	0.4146	0.4365	0.4889	0.3183	0.2307	0.2226	0.1949	0.2746
LV_2	0.4149	0.4175	0.4365	0.3907	0.6028	0.5150	0.6266	0.6666
LV_3	0.4307	0.4681	0.4884	0.3355	0.4903	0.5492	0.3866	0.5353
LV_4	0.5901	0.6380	0.6115	0.5210	0.4992	0.5219	0.4072	0.5685
LV_5	0.5668	0.5243	0.6520	0.5240	0.5387	0.5880	0.4434	0.5848
Estonia	0.5367	0.5516	0.5610	0.4975	0.4914	0.4847	0.4468	0.5428
Latvia	0.4834	0.4969	0.5355	0.4179	0.4723	0.4793	0.4117	0.5260
Lithuania	0.5610	0.5953	0.5966	0.4912	0.3213	0.3573	0.2620	0.3446
Baltics	0.5266	0.5467	0.5631	0.4702	0.4363	0.4462	0.3823	0.4803

Linear trends of CAE and POE obtained for 2012–2021 are presented in Table 5. Obviously, the trend coefficients for POE are higher than those for CAE. This conclusion is valid for most of the country-method-indicator combinations.

The minimum, maximum and average CAE scores are presented in Figure 2. Similarly, the POE scores are summarized in Figure 3. These results imply that Lithuanian banks are on average better in attracting clients (and deposits) if compared to Estonian and Latvian banks. However, Lithuanian banks show lower profit-oriented efficiency.

Table 5. Trend of CAE and POE utility values by bank and country

Bank	Trend of CAE Utility				Trend of POE Utility			
	Average	SAW	TOPSIS	EDAS	Average	SAW	TOPSIS	EDAS
EE_1	0.0325	0.0290	0.0388	0.0297	0.0040	0.0131	–0.0046	0.0034
EE_2	–0.0087	–0.0212	–0.0047	–0.0001	–0.0444	–0.0490	–0.0339	–0.0503
EE_3	0.0131	0.0161	0.0106	0.0126	0.0600	0.0675	0.0475	0.0650
EE_4	0.0068	0.0144	0.0003	0.0059	–0.0092	–0.0055	–0.0094	–0.0126
EE_5	0.0421	0.0520	0.0382	0.0362	–0.1070	–0.1112	–0.1017	–0.1082
EE_6	–0.0110	–0.0227	–0.0040	–0.0064	0.0180	0.0130	0.0200	0.0211
EE_7	0.0149	0.0366	0.0012	0.0067	0.0612	0.0774	0.0466	0.0595
LT_1	–0.0016	–0.0194	0.0115	0.0031	0.1041	0.1023	0.0823	0.1278
LT_2	–0.0196	–0.0165	–0.0169	–0.0253	0.0266	0.0295	0.0226	0.0276
LT_3	–0.0450	–0.0739	–0.0222	–0.0390	–0.0189	–0.0248	–0.0088	–0.0232
LT_4	0.0064	0.0176	0.0009	0.0008	0.0049	0.0009	–0.0014	0.0151
LT_5	–0.0198	–0.0092	–0.0266	–0.0237	–0.0116	–0.0087	–0.0055	–0.0207
LV_1	0.0041	0.0066	0.0038	0.0018	0.0257	0.0162	0.0223	0.0387
LV_2	0.0036	0.0220	0.0098	–0.0209	–0.0708	–0.0431	–0.0931	–0.0763
LV_3	0.0065	0.0063	0.0041	0.0092	0.0681	0.0788	0.0553	0.0704
LV_4	0.0250	0.0351	0.0157	0.0241	0.0046	0.0042	0.0073	0.0024
LV_5	–0.0024	0.0056	–0.0050	–0.0077	0.0345	0.0289	0.0284	0.0462
Estonia	–0.0025	–0.0018	–0.0032	–0.0026	0.0106	0.0146	0.0081	0.0089
Latvia	0.0074	0.0151	0.0057	0.0013	0.0124	0.0170	0.0040	0.0163
Lithuania	–0.0178	–0.0178	–0.0151	–0.0204	0.0018	0.0032	0.0015	0.0008
Baltics	–0.0037	–0.0012	–0.0039	–0.0061	0.0105	0.0132	0.0070	0.0113

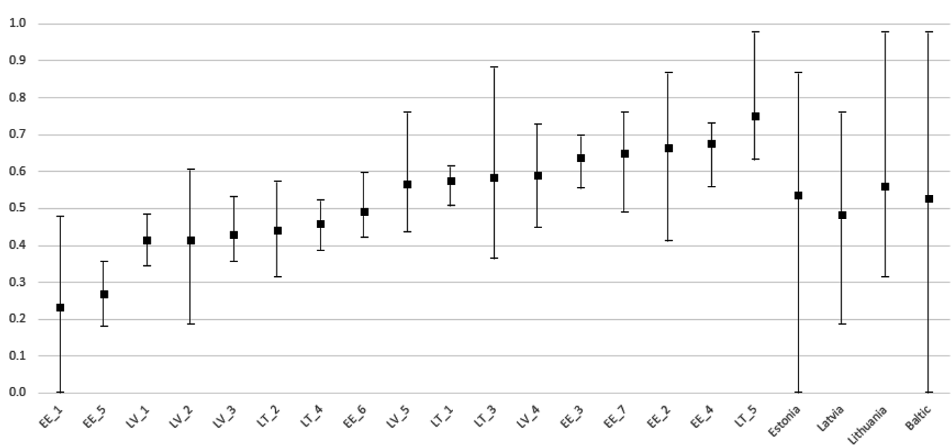

Figure 2. CAE scores for the Baltic banks (minimum, average, and maximum values over 2012–2021)

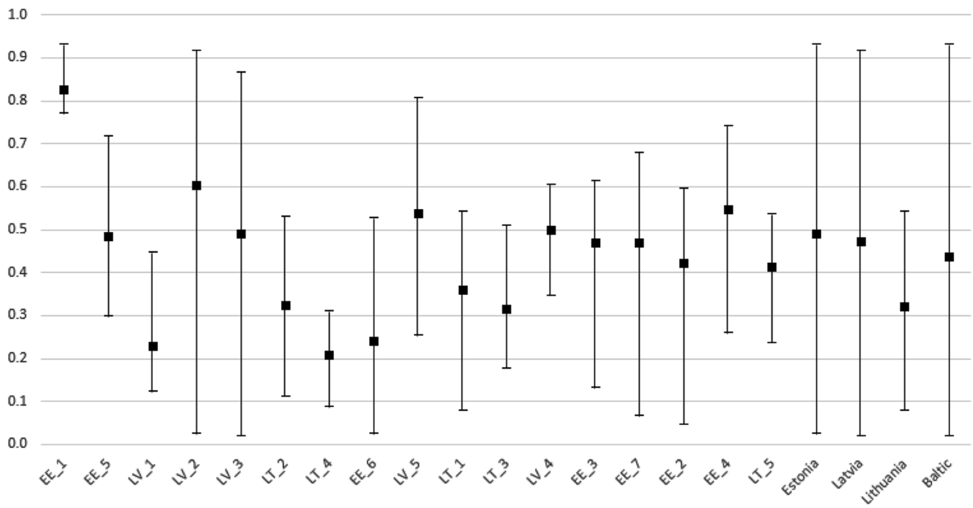

Figure 3. POE scores for the Baltic banks (minimum, average, and maximum values over 2012–2021)

The variation of CAE utilities score is lower than variation of POE utilities score. Coefficients of variation are 0.32 and 0.50 respectively. This conclusion holds for 15 of 17 banks. The consistent CAE utilities scores suggest that it is more challenging to increase efficiency from a client perspective compared to the profit generation perspective.

When banks are divided into four groups based on CAE and POE scores (Figure 4), the average Estonian bank falls among the best banks with better than average both CAE and POE scores. Meanwhile, the average bank in Lithuania would be among those banks that are better than average in attracting customers, but less oriented towards profit. The average Latvian bank has less than average client attraction score and better than averages profit generation score. Notable, none of Lithuanian banks reached a better than average profit-oriented efficiency score.

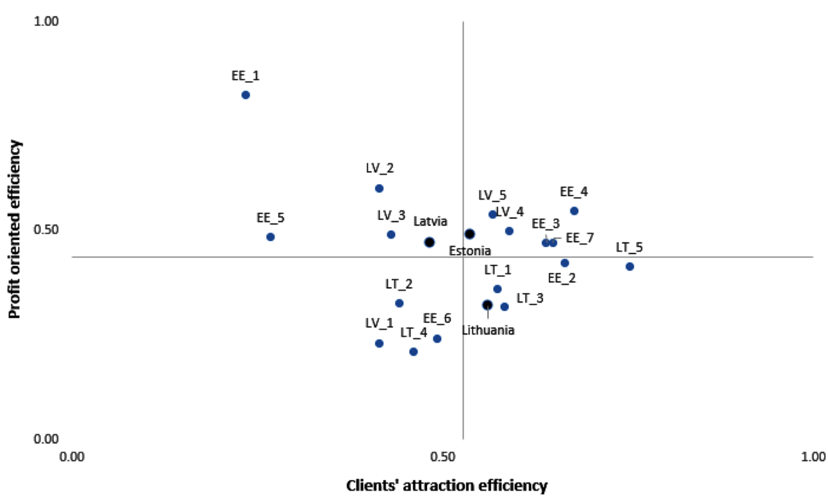

Figure 4. Relationship between the average CAE and POE scores for the Baltic banks (2012–2021)

Over the decade the average bank in Latvia and Estonia improved both from client attraction perspective and from orientation to profit perspective. Latvia's average bank shows the substantial improvement of CAE score. The distribution of banks by linear trends of the POE and CAE scores is presented in Figure 5. The average bank in Lithuania shows the negative trend in CAE and POE. It is worth reminding that even with the negative trend of the change of the CAE score, the average Lithuanian bank has the best CAE score than the banks of other Baltic countries.

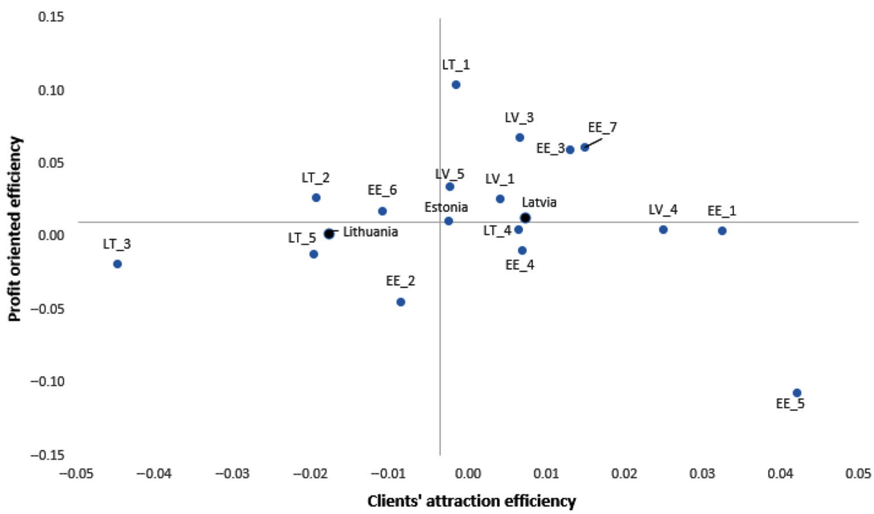

Figure 5. Relationship between trends for the CAE and POE scores for the Baltic banks (2012–2021)

Rather low correlation was detected between the COE and POE utility scores based on three MCDM methods. The high utility (performance) in terms of customer attraction does not correspond to high utility in profit orientation, and vice versa. The correlation coefficient between CAE and POE composite utilities scores was –0.09. Among the three MCDM methods used for construction of composite utility scores, TOPSIS showed the moderate negative correlation of –0.31 (against results rendered by the other MCDM methods). SAW and EDAS show virtually no correlation with corresponding 0.06 and 0 correlation coefficients. The results can be affected by the general economic conditions. Negative interest rates discourage saving, while excess liquidity in the banking sector makes it easier to attract deposits.

The rating of the average country's bank from a client attractiveness perspective underwent changes throughout the analyzed decade. Figure 6 shows that the average Latvian bank had the most significant improvement in their client attraction utility score, while the average Lithuanian bank faced the significant drop in client attractiveness utilities score. In 2012, Lithuanian banks were clearly in a better position compared to Estonian and Latvian banks. However, the CAE utilities score of Lithuanian banks decreased in 2017–2018, and by 2021, the average bank in Lithuania ranked the last among the Baltic countries' average banks. In terms of rankings, the Estonian bank claims the first position in 2021, followed by the Latvian bank in second place, and the average Lithuanian bank has the third ranking. Please note the ranking in 2012–2021 period (Figure 6) is different: Lithuanian, Estonian, and Latvian average banks appear in that order.

The CAE utilities scores of Baltic countries banks converged in 2019 and the gap between the utilities scores is not as large as at the beginning of the period. This indicates that banks became similar from client attraction perspective.

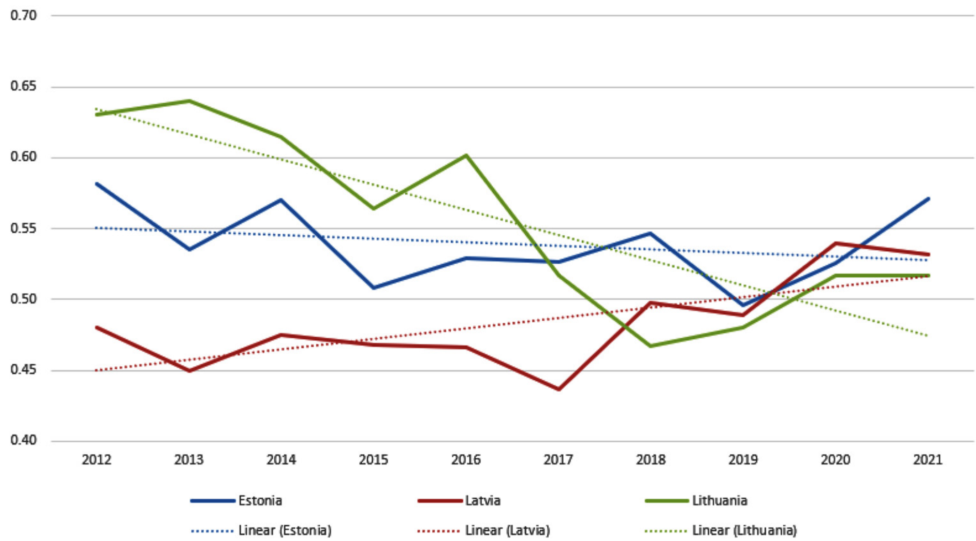

Figure 6. Average CAE scores across the Baltic countries (2012–2021)

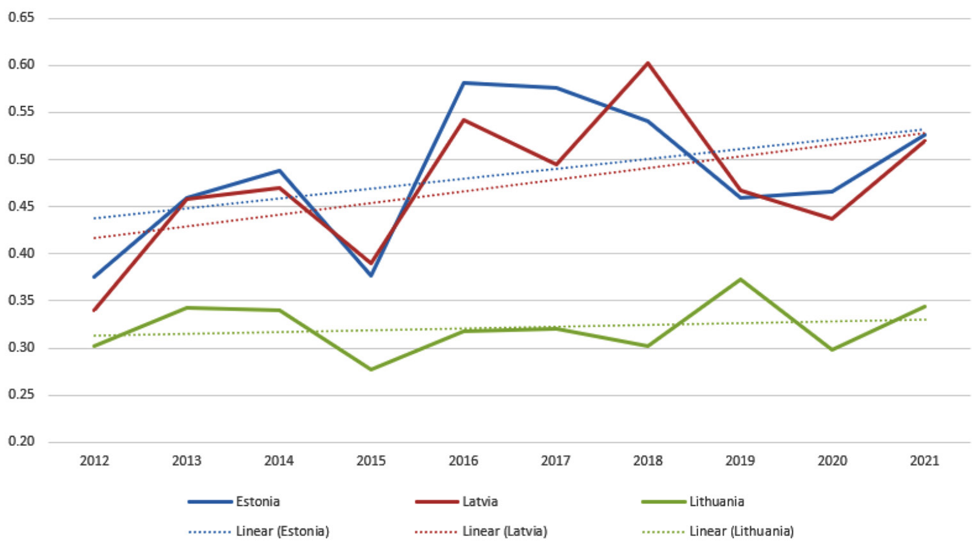

Figure 7. Average POE scores across the Baltic countries (2012–2021)

The rating of the average country's bank from orientation to profit perspective was similar in 2012–2021. Figure 7 shows that all three average Baltics banks improved their profit generation utility scores, though the average Latvian bank has the most significant improvement in this score. During the whole period the average Lithuanian bank was behind the Estonian and Latvian banks. In terms of rankings, the Estonian bank claims the first position in 2021, followed by the Latvian bank in second place, and the average Lithuanian bank has the third ranking. The ranking in 2012–2021 period (Figure 7) is the same. The POE scores for Estonian and Latvian banks are very similar throughout the analyzed period.

5. Sensitivity analysis

Up to now, we assumed equal importance of the three MCDM methods viz., SAW, EDAS, and TOPSIS, in Eq. 14. We further seek to assess if changes in the weights assigned for the MCDM methods are likely to affect the results. Therefore, we change the weights by assigning a weight of 50% for a certain method and splitting the remaining 50% equally between the rest. As a result, three additional scenarios are created for CAE and POE. The results are provided in Table 6.

Table 6. Sensitivity analysis (the weights assigned to MCDM methods are perturbed)

Scenario	CAE1	CAE2	CAE3	CAE4	POE1	POE2	POE3	POE4
Weights, ω_ξ								
SAW	1/3	1/2	1/4	1/4	1/3	1/2	1/4	1/4
TOPSIS	1/3	1/4	1/2	1/4	1/3	1/4	1/2	1/4
EDAS	1/3	1/4	1/4	1/2	1/3	1/4	1/4	1/2
Correlation								
CAE2	0.998517	1						
CAE3	0.998464	0.995422	1					
CAE4	0.998563	0.995591	0.995632	1				
POE2					0.996184	1		
POE3					0.997352	0.987503	1	
POE4					0.999687	0.994903	0.99731	1

Results of the sensitivity analysis suggest that the changes in the weights assigned to the three MCDM methods do not have a decisive impact on the aggregate utility scores. Looking at the CAE, the lowest correlation coefficient for the aggregate utility scores obtained by using different weighting schemes is higher than 0.99. For the POE, the same result is obtained.

6. Conclusions

The paper proposed a framework for analysis of the bank performance from the viewpoint of the client attraction and profit generation. The first viewpoint relates to the ability to attract the deposits that can further be used for intermediation and revenue generation. This second stage is reflected in the profit generation viewpoint. The case of the banks operating in the Baltic States was used as an empirical example. The proposed approach involved an indicator set and several MCDM methods.

The results suggest that the Baltic banks operated at different levels of client attraction and profit generation as measured by the three MCDM methods. The three MCDM methods used for the analysis implied similar performance scores. At the bank-level, the variability of the profit generation scores was higher than that of the client attraction scores. This indicates that Baltic banks are more diverse in the sense of their business operations and their profitability if opposed to the client attraction indicators.

The results also imply that there is no correlation between client attraction and profit generation in the case of Baltic banks. These results suggest that banks may not be able to offer attractive solutions and generate high profits simultaneously. This calls for the development of novel business models that would allow us to provide attractive customer services and ensure high profitability.

The present research features certain limitations. First, the weights of the criteria were assumed to be equal. Even though it is not likely that the criteria weights would change too much in the presence of ten criteria, further research could employ data-driven or expert-based solutions for weight elicitation. Furthermore, stochastic MCDM approaches could be applied to account for statistical noise and further improve robustness of the analysis.

Author contributions

Conceptualization – K. K.; methodology – K. K. and T. B.; software – K. K.; validation – D. S.; formal analysis – K. K. and D. S.; investigation – K. K. and T. B.; data curation – K. K. and D. S.; writing – original draft – K. K.; writing – review & editing – T. B. and D. S.; visualization – K. K.; supervision – T. B.

Disclosure statement

The authors declare no conflict of interest.

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