REM WORKING PAPER SERIES

Efficiency of the European Union Banking Sector: A Panel Data Approach

Cândida Ferreira

REM Working Paper 0354-2024

October 2024

REM – Research in Economics and Mathematics
Rua Miguel Lúpi 20,
1249-078 Lisboa,
Portugal

ISSN 2184-108X

REM – Research in Economics and Mathematics

Rua Miguel Lupi, 20
1249-078 LISBOA
Portugal

Telephone: +351 - 213 925 912
E-mail: rem@iseg.ulisboa.pt

https://rem.rc.iseg.ulisboa.pt/

https://twitter.com/ResearchRem

https://www.linkedin.com/company/researchrem/

https://www.facebook.com/researchrem/

Efficiency of the European Union Banking Sector: A Panel Data Approach

Cândida Ferreira*

ISEG, UL – Lisbon School of Economics and Management of the Universidade de Lisboa
UECE - Research Unit in Complexity and Economics
REM – Research in Economics and Mathematics
LISBOA, PORTUGAL
candidaf@iseg.ulisboa.pt

Abstract

This study uses Data Envelopment Analysis to analyse the evolution of the efficiency of the European Union banking sector with different concepts and measures of bank efficiency, as well as the results provided by the Malmquist index to measure different efficiency changes, and the total productivity changes considering a panel of 784 relevant banks from all the 27 European Union countries, between 2006 and 2021. Banks are assumed to produce three outputs: loans, other earning assets, and non-earning assets using three inputs: interest expenses, non-interest expenses, and equity, overall, the findings of the paper point to the existence of inefficiencies which are mainly justified by non-optimal combinations of the considered inputs and outputs, and not by the scale of the production. The results obtained also reveal that the EU banks included in the sample have room to improve their choices of the combinations of inputs to produce the desired outputs at minimum costs. The values of the computed Malmquist index indicate overall progress, except during the period of the global financial crisis, and to some extent also between the years 2015-2017, corresponding to a turbulent period of the EU banking sector with the advancements of the European Banking Union and two relevant initiatives: the European Banking Supervision and the Single Resolution Mechanism.

Keywords: Data Envelopment Analysis; European Union banking sector; bank efficiency; Malmquist index.

JEL Classification: C33; D53 ; F36 ; G21.

* The author acknowledges financial support from FCT – Fundação para a Ciência e Tecnologia (Portugal), national funding through research grant UIDB/05069/2020

1. Introduction

Over decades, and particularly after the last global financial crisis and the sovereign debt crisis that affected many European Union (EU) countries, the EU banking sector had to face significant challenges in adaptation to the new economic and financial reality. The EU banks were obliged to adapt to the reshaped bank market regulations and the supervision of the banks, and they have been struggling for their profitability in a very strict environment, including the historically low interest rate levels.

The efficiency of the EU banks go on being relevant not only to the banking sector but also to the whole EU economic system, namely because in Europe banks are still the largest providers of credit to producers and households. The good performance of banks is also important to improve the transmission of monetary policy, ensuring the required lending volumes at sustainable lending rates.

There is a large strand of literature analysing the efficiency of the EU banks using frontier methods and estimating efficient production frontiers with parametric and non-parametric approaches. Some of these studies use the Stochastic Frontier Analysis, a parametric approach which is based on a problem of optimisation, that is, the maximisation of the profit or the minimisation of the costs, given the assumption of a stochastic optimal frontier (among others, Lozano-Vivas et al, 2011; Vozková and Kuc, 2017; Kuc, 2018: Huljak et al, 2022).

Data Envelopment Analysis (DEA) is one of the most used non-parametric approaches to estimate efficient production frontiers. It is based on a linear programming methodology that is appropriate to measure the efficiency of different decision-making units (DMUs) using multiple inputs and outputs in a production process. DEA has been used to analyse the efficiency of European banks in single-country studies (such as Tanna et al, 2011; Ouenniche and Carrales, 2018) as well as in multi-country studies (for example, Chortareas et al, 2013; San-Jose et al, 2018; Kolia and Papadopoulos, 2022).

This paper uses DEA techniques to measure the efficiency of a relatively large panel of 784 relevant banks of all the 27 European Union (EU) countries between 2006 and 2021, considering different concepts of efficiency: technical efficiency, pure technical efficiency, scale efficiency, cost efficiency, and allocation efficiency, as well as the results provided by the Malmquist indices to measure the different efficiency changes, and the total productivity changes.

The results of the computed technical efficiency (with constant returns to scale), the pure technical efficiency (with constant returns to scale), and the scale efficiency reveal that the technical inefficiency of the considered EU banks is mainly justified by non-optimal combinations of the considered inputs and outputs, and not by the scale of production. The findings of the paper also show that the allocative efficiency is always higher than the cost efficiency, revealing that the EU banks included in the sample have room to improve their choices of the combinations of inputs to produce the desired outputs at minimum costs.

The performed estimates allow the presentation of rankings lists with the classification of the sub-samples of the banks from each EU country included in the panel, according to the results of their technical (and pure technical) efficiency, cost efficiency, and allocative efficiency. Although there is no evident conclusion that the sub-sample of banks from one specific EU country is always more efficient than the other EU banks, it is still possible to compare their positions in the different ranking lists and to identify the ones that are often included in the top position.

The values of the computed Malmquist index overall reveal progress, except during the period of the global financial crisis, and to some extend also between the years 2015-2017, corresponding to a turbulent period of the EU banking sector with the advancements of the European Banking Union and two relevant initiatives: the European Banking Supervision and the Single Resolution Mechanism.

The paper proceeds as follows: Section 2 presents some relevant literature; Section 3 introduces the adopted methodology and the used data; Section 4 presents the results obtained; Section 5 concludes.

2. Relevant Literature

The studies on bank efficiency mainly follow the strand of literature that considers the possibility of defining an efficiency frontier as the best combination of the required inputs to get the desired outputs. The firm's efficiency is therefore the deviation of its position from a defined efficiency frontier, which can be obtained with parametric and non-parametric approaches.

Data Envelopment Analysis (DEA) is one of the most used non-parametric approaches that was first introduced by Charnes et al (1978) and developed among others by Ali and Seiford (1993), Lovell (1993), Cooper et al (2006), Cook et al (2014). DEA is based on a linear programming methodology that is appropriate to measure the efficiency of different decision-making units (DMUs) using multiple inputs and outputs in a production process. It has been used often to assess and compare the efficiency performance of banks in different countries or regions, including the European banking institutions, both in focused studies and in multi-country focussed studies.

Examples of single-focused DEA studies include Favero and Papi (1995) who provided measures of the technical and scale efficiencies in the Italian banking industries by implementing non-parametric DEA on a cross-section of 174 Italian banks taken in 1991. The conclusions pointed to the existence of both technical and allocative efficiency; in addition, when regression analysis was used, bank efficiency was best explained by productive specialization, size and, to a lesser extent, location.

Drake (2001) analysed relative efficiencies within the banking sector and the productivity change in the main UK banks over the period 1984 to 1995. The results obtained provided important insights into the size-efficiency relationship in the considered sample of banks and offered a perspective on the evolving structure and competitive environment within which the banks are currently operating. Webb (2003) utilised DEA window analysis, to measure the relative efficiency levels of large UK retail banks during the period 1982-1995, mostly finding that the overall long-run average efficiency trend was falling, and also that all banks in the study showed reducing levels of efficiency over the entire period.

Tanna et al (2011) considered a sample of 17 banking institutions operating in the UK between 2001 and 2006 and used DEA techniques to provide empirical evidence on the association between the efficiency of UK banks and board structure, namely board size and composition. They found some evidence of a positive association between board size and efficiency as well as robust evidence that board composition had a significant and positive impact on all measures of efficiency.

Ouenniche and Carrales (2018) also assessed the efficiency profiles of UK banks, collecting data from 109 commercial banks over the years 1987-2015, and concluded that, on average, commercial banks operating in the UK were yet to achieve acceptable levels of overall technical efficiency, pure technical efficiency, and scale efficiency.

Examples of multi-country DEA studies analysing the efficiency of the European banks include Casu and Molyneux (2003) who considered a sample of 750 from five EU countries (France, Germany, Italy, Spain and the UK) to investigate the existence of improvement and the potential convergence of efficiency across the European banking markets in the aftermath of the creation of the Single Internal Market with efficiency measures obtained with DEA estimations. The main findings of this work suggested that there was a small improvement in the bank efficiency levels but there was no convincing evidence to support the convergence of the EU banks' productive efficiency.

Chortareas et al (2013) used a large sample of commercial banks operating in 27 EU member states over the 2000s and with data sourced from the Bankscope database, they estimated bank-specific efficiency scores with DEA. The paper investigated the dynamics between the obtained bank efficiency levels and the financial freedom counterparts of the economic freedom index drawn from the Heritage Foundation database. The main findings suggested that the higher the degree of a country's financial freedom, the higher the benefits for the banks located in the country, in terms of cost advantages and overall efficiency.

Degl'Innocenti et al (2017) used a two-stage DEA model to analyse the efficiency of 116 banks from nine Central and Eastern European (CEE) countries, members of the EU, covering the period 2004-2015. In the first stage, they included total assets and personnel expenses as two inputs, while deposits were considered as the output of the "value-added activity". Deposits then entered the second stage (the "profitability activity") as inputs, whereas loans and securities were the final outputs. Overall, the findings of the paper indicated a low level of efficiency over the entire period of analysis, especially for Eastern European and Balkan countries. Moreover, the paper concluded that inefficiency in CEE countries was mainly driven by the profitability stage rather than the value-added activity stage.

Asmild and Zhu (2016) analysed the risk and efficiency of the European banks considering a sample of 71 banks from 20 different EU member-states for the years 2006-2009 and data collected directly from each bank's audited financial report. Aiming to analyse the impact of the proposed weight restrictions, they estimated two DEA models: the "Funding mix model", including five inputs (Retail funding expenses, Wholesale funding expenses, Physical capital expenses, Personnel expenses, and Impaired loan) and two outputs (Loans, and Financial assets), and the "Asset mix model", also considering five inputs (Property loan, Non-property loan, Trading financial assets, Non-trading financial assets, and Impaired loan), and two outputs (Income, and Provision for impaired loan loss). The findings reveal that using a more balanced set of weights tended to reduce the estimated efficiency scores more for those banks which were bailed out during the financial crisis, highlighting some potential bias and limitations of the DEA estimations, and showing that the decreases in efficiency scores after weight restrictions were significantly higher for the bailed-out banks than for the non- bailed-out banks.

Kocisova (2017) used DEA estimations to analyse the efficiency of the banking sectors in the European Union countries in 2015 with data compiled from the database of the European Central Bank. The results obtained with the DEA estimations revealed the large banking sectors appear to be most efficient. Moreover, the paper highlighted the benefits of using DEA as it provides recommendations on how banks should adjust the structure of their inputs and outputs, taking into account output prices, which should result in a shift to the efficiency frontier. On the other hand, the paper also highlighted some potential disadvantages of the DEA method as it is used to calculate relative efficiency, within the selected group of decision-making units (DMUs), and under the selected group of variables (input, output, and prices of the outputs), therefore, a change in the group of DMUs or used variables, can lead to a change in the efficiency frontier as well as in the level of efficiency obtained for each DMU

San-Jose et al (2018) studied the relationship between economic efficiency and sustainability of banking in Europe, applying DEA techniques to a sample of 2752 financial institutions (separately analysing three types of banks: commercial, cooperative, and saving banks) from EU-15 countries in 2014. The main findings of the paper highlighted that European banking was not yet harmonized, providing also evidence that there was no trade-off between social efficiency and economic efficiency. Moreover, the paper contributed to the discussion of the strengths and weaknesses of the DEA approach, emphasising that DEA is extremely flexible as there is no pre-established relation between input and outputs, and this permits a quasi-real show of the relationship between variables. However, DEA is also an extreme form and deterministic method that assumes that if a DMU levels output with input, other DMUs should reach the same level; also, the variable selection is of fundamental importance as there are no suitable tests to estimate if the results of the analysis are stable or would vary significantly with other variables.

Kolia and Papadopoulos (2022) investigated the development of bank efficiency and the progress of banking integration between 2013 and 2018, examining whether banking integration among the Euro area countries has developed more than that of the total sum of European countries. They also compared the evolution of efficiency and the progress of banking integration across the Euro area countries with that of the United States. Bank efficiency was measured with DEA estimations, considering three inputs: labour, capital, and deposits, and two outputs: loans and net interest income. The findings showed that the efficiency of the US banking system was considerably higher than that of the Euro area and the EU banks. Moreover, the paper concluded that overall, there was no evidence of convergence across the reported banking groups.

3. **Methodology and data**

The paper uses Data Envelopment Analysis (DEA), a well-tested non-parametric efficiency approach to measure the efficiency of different decision-making units (DMUs), using multiple inputs and outputs in a production process. Despite the recognition that the results obtained with this methodology are very sensitive to the chosen inputs and outputs, as well as that the number of efficient DMUs tends to increase with the inclusion of more input and output variables, DEA is still considered appropriate to measure efficiency, including bank efficiency. In comparison with other tested methodologies, it presents some advantages, such as the possibility of handling multiple inputs and outputs without an explicit definition of a production function, the possibility of being used with any input-output measurement, and the possibility of obtaining efficiency (and inefficiency) measures for every DMU.

DEA is based on a linear programming methodology that was first developed by Charnes et al (1978) and developed among others by Ali and Seiford (1993), Lovell (1993), Charnes et al (1994), and Cooper et al (2006). Nowadays DEA is a well-tested non-parametric efficiency approach, based on a linear programming methodology that is appropriate to measure the efficiency of different decision-making units (DMUs) using multiple inputs and outputs in a production process.

The model proposed by Charnes et al (1978) is based on the assumption of constant returns to scale and is very well presented in Coelli (1996) assuming that each of the considered N firms (or DMUs) use K inputs to produce M outputs, being X the KxN input matrix and Y the MxN output matrix that include the data of all the N DMUs. Using linear programming, one of the ways to measure the efficiency is by solving the problem:

$$Min_{\theta,\lambda}\ \theta,$$

Subject to: $-y_i + Y\lambda \geq 0;\ \ \theta y_i - X\lambda \geq 0;\ \ \lambda \geq 0$ **(1)**

(where θ is a scalar and λ is a $Nx1$ vector of constants).

Solving this problem, we obtain, for each DMU, the efficiency score θ. In all situations $\theta \leq 1$; when $\theta=1$ the correspondent DMU is in the efficient frontier, and when they are not in the frontier the values of $1-\theta$ represent the distance to this frontier or the measure of their technical inefficiencies.

Under these conditions, the technical efficiency of each DMU is a comparative measure of how well it processes the inputs to obtain the desired outputs in comparison with the best-achieved performance that is represented by the production possibility frontier. This overall efficiency measure depends not only on the input/output specific combination (representing the pure technical efficiency) but also on the scale of the production operation (or the scale efficiency).

Still following Coelli (1996), we can introduce the assumption of variable returns to scale including the convexity constrain $N1'\lambda = 1$ in the model (1) and solve the following linear programming problem to obtain the measure of the pure technical efficiency:

$$Min_{\theta,\lambda}\ \theta,$$

Subject to: $-y_i + Y\lambda \geq 0;\ \ \theta y_i - X\lambda \geq 0;\ \ N1'\lambda = 1;\ \ \lambda \geq 0$ **(2)**

(where θ is a scalar, λ is a $Nx1$ vector of constants, and $N1$ is a $Nx1$ vector of ones).

Under the assumption of variable returns to scale the measure of (pure) technical efficiency basically captures the managerial performance. The scale efficiency represents the ability of the management to choose the scale of the production and can be obtained as the ratio of the overall technical efficiency (under the assumption of constant returns to scale) and the pure technical efficiency (see, among others, Kumar and Gulati, 2008; Fujii et al, 2018).

To obtain the allocative efficiency, first, it is necessary to get the cost efficiency measure, solving the problem:

$Min_{\lambda,xi^*}\ w_i\ 'x_i^*,$

Subject to: $-y_i + Y\lambda \geq 0;\quad x_i^* - X\lambda \geq 0;\ N1'\lambda = 1;\ \lambda \geq 0$ **(3)**

(where w_i is a vector of the prices of the inputs of the i-th DMU, x_i * is the cost-minimising vector of the input quantities for the i-th DMU, given the input prices x_i, and the output levels y_i).

Solving this problem, it is possible to obtain the value of the cost efficiency of the i-th DMU as the ratio of the minimum cost to the observed cost of this DMU, $w_i\ '\ x_i^*/\ w_i\ '\ x_i$. Moreover, and as well demonstrated in Coelli (1996), the allocative efficiency (AE) is obtained as the ratio of the cost efficiency (CE) to the technical efficiency (TE), that is AE=CE/TE.

When considering panel data, we can also use a DEA linear programme to get a Malmquist index that measures the productivity change, decomposing it into the technical change and the technical efficiency change (see among others, Candemir et al, 2011) the Malmquist productivity change index between the period t and the period t+1 can then be defined as

$$m(y_{t+1}, x_{t+1}, y_t, x_t) = \left[\frac{d^t(x_{t+1}, y_{t+1})}{d^t(x_t, y_t)} \times \frac{d^{t+1}(x_{t+1}, y_{t+1})}{d^{t+1}(x_t, y_t)}\right]^{1/2} \qquad (\mathbf{4})$$

This index can be decomposed into the

Efficiency Change (EC) = $\frac{d_0^{1+1}\ (x^{1+1}, y^{1+1})}{d_0^1\ (x^1, y^1)}$ $(\mathbf{5})$ and the

Technical Change (TC) = $\left[\frac{d_0^t(x_{t+1}, y_{t+1})}{d_1^{t+1}(x_{t+1}, y_{t+1})} \times \frac{d_0^t(x_t, y_t)}{d_1^{t+1}(x_t, y_t)}\right]^{1/2}$ $(\mathbf{6})$

Overall, it is generally recognised that DEA is an appropriate method to analyse and measure efficiency, including bank efficiency, and that in comparison with other tested methodologies, it presents some advantages, such as the possibility of handling multiple inputs and outputs without an explicit definition of a production function, the possibility to be used with any input-output measurement, and the possibility to obtain efficiency (and inefficiency) measures for every DMU.

On the other hand, DEA has also some recognised disadvantages, namely the fact that we cannot test for a better specification, as well as the fact that the results are very sensitive to the chosen inputs and outputs, as the number of efficient DMUs tend to increase with the inclusion of more input and output variables (see, for example, Ali and Lerme, 1997; Johnes, 2006; Berg, 2010).

In this paper, banks are assumed to produce three outputs: loans, other earning assets, and non-earning assets using three inputs: interest expenses, non-interest expenses, and equity. The inclusion of equity aims to take into account the relevance of the risk preferences when estimating efficiency (see, for example, Altunbas et al, 2007; Almanza and Rodríguez, 2018).

To estimate the cost efficiency, it is also necessary to get information regarding the costs of production. Here these costs are proxied first, with the ratio of the interest expenses to the deposits and short-term funding (representing the price of the borrowed funds); second, the price of the capital and labour is proxied by the ratio of the non-interest expense to total assets; third, the ratio of the equity to total assets, representing the price of the equity.

Under these conditions, the aim will be to choose the best combination of inputs to produce the outputs at minimum cost. Following the adopted methodology, allocative efficiency (AE) will be the ratio of the cost efficiency (CE) to the technical efficiency (TE), and it is possible to consider either constant return to sale (CCR) or variable return to scale (VRS).

The information regarding the considered bank outputs, inputs, and production costs, was sourced from the Moody's Analytics BankFocus database in December 2022 and the paper includes a relatively large panel of 784 relevant banks of all the 27 European Union (EU) countries between 2006 and 2021. The choice of the banks took into consideration not only the availability of the data but also the size of the banks, as the size of the banks is likely to affect their behaviour. Overall, banks with less than 2 billion Euros of total assets in 2021 were excluded from the sample. However, for the EU countries with few banks with a high amount of total assets, the sample includes banks with less than 2 billion Euros of total assets (but not far from 1 billion Euros in 2021). Table 1 indicates the number of banks for each of the 27 EU countries included in the sample, as well as their representativeness not only in terms of the percentage of the total number of the banks included in the whole sample but also in terms of their percentages of the total deposits and of the total loans provided to costumers.

Table 1 – Number of the considered banks by European Union member-state and their representativeness

EU country	Number of banks	% of the total banks	% of the deposits in 2021	% of the provided loans in 2021
Austria	27	3.44	2.62	2.44
Belgium	19	2.42	3.66	3.37
Bulgaria	9	1.15	0.20	0.14
Croatia	4	0.51	0.21	0.14
Cyprus	5	0.64	0.42	0.30
Czech Rep.	12	1.53	0.96	0.70
Denmark	15	1.91	1.17	1.85
Estonia	4	0.51	0.09	0.08
Finland	7	0.89	1.39	1.81
France	129	16.45	31.05	32.97
Germany	322	41.07	26.82	26.30
Greece	6	0.77	0.76	0.50
Hungary	6	0.77	0.44	0.29
Ireland	6	0.77	1.23	0.82
Italy	63	8.04	9.66	9.68
Latvia	5	0.64	0.08	0.05
Lithuania	4	0.51	0.13	0.07
Luxembourg	34	4.34	1.33	0.94
Malta	7	0.89	0.12	0.07
Netherlands	16	2.04	6.68	7.28
Poland	18	2.30	1.47	1.16
Portugal	12	1.53	1.27	0.94
Romania	6	0.77	0.30	0.19
Slovakia	5	0.64	0.19	0.20
Slovenia	7	0.89	0.17	0.11
Spain	28	3.57	5.55	4.74
Sweden	8	1.02	2.05	2.84

Source: Author's calculations using data sourced from the Moody's Analytics BankFocus database.

4. Empirical Results

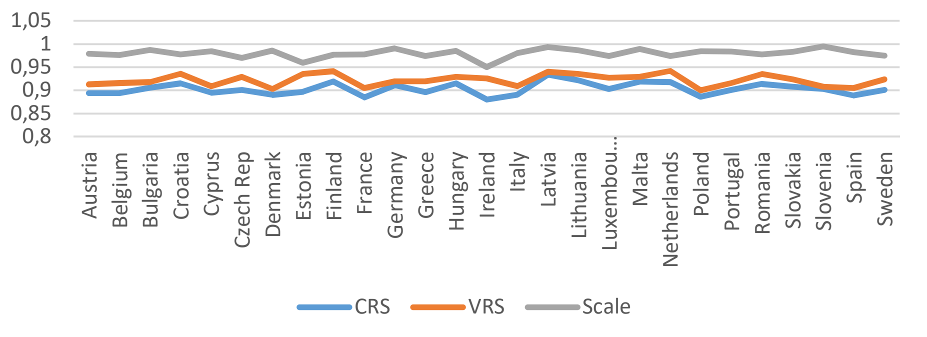
The paper first reports the results of each EU country's bank technical efficiency (with constant returns to scale), the pure technical efficiency (with variable returns to scale), and the scale efficiency, during the considered period. Secondly, the paper presents the values of the cost and allocative efficiencies, with both constant and variable returns to scale. In the third step, the paper presents the countries' ranking lists according to the scores obtained for the three measures of bank efficiency (technical, cost, and allocative efficiencies) also considering constant and variable returns to scale. Finally, the paper provides the results of the computed Malmquist indices, measuring the technical, technological, and scale efficiency changes, as well as the total productivity changes.

4.1.Technical Efficiency, Pure Technical Efficiency, and Scale Efficiency

The technical efficiency measure (with constant returns to scale) for the whole sample of 784 EU banks during the period 2006-2021 is TE_{CRS} = 0.903, while the pure technical efficiency (with variable returns to scale) is TE_{VRS} = 0.922, revealing that the technical inefficiency of the European banks included in our sample is mainly due to inefficient managerial performance and non-efficient combinations of the considered inputs and outputs. The scale efficiency represents the ability of the management to choose the scale of the production and can be obtained with the ratio TE_{CRS} / TE_{VRS}. Here the scale efficiency of the whole sample is 0.980, indicating that overall, the scale of production of the considered EU banks is not very far away from the most productive scale size.

Figure 1 presents the results obtained for the technical efficiency, pure technical efficiency, and scale efficiency of the considered banks of all EU member states, between 2006 and 2021. In line with the results reported for the whole sample of EU banks, there is clear evidence that the scale of the bank production is overall appropriate and bank efficiency is always higher when considering variable returns to scale.

Figure 1 - Technical efficiency (with CRS), pure technical efficiency (with VRS) and scale efficiency



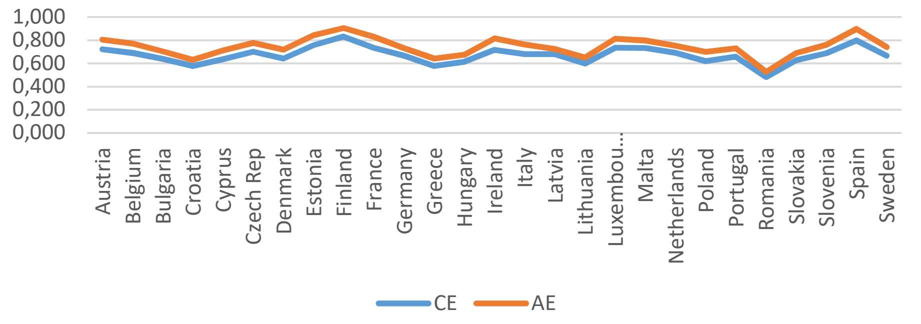
Source: Author's calculations.

4.2.Cost Efficiency and Allocative Efficiency, with Constant and Variable Returns

As already mentioned, cost efficiency represents the selection of the necessary inputs, considering their prices, more precisely, the choice of the best combinations of inputs to produce the outputs at minimum cost. Following the methodology presented in the previous section, allocative efficiency (AE) will be the ratio of the cost efficiency (CE) to the technical efficiency (TE), either with constant returns to scale or variable returns to scale.

Considering constant returns to scale, and the whole sample of 784 EU banks over the years 2006-2021 the cost efficiency is $CE_{CRS} = 0.671$ and the allocative efficiency is $AE_{CRS} = 0.744$. The results obtained with variable returns to scale are $CE_{VRS} = 0.731$ and $AE_{VRS} = 0.793$, confirming that bank efficiency is higher when the scale of the bank production is not constant. The results also reveal that the cost efficiency is much lower than the technical efficiency and therefore, there is evidence of allocative inefficiency, that is, the inability of the EU banks to allocate funding to the most productive uses.

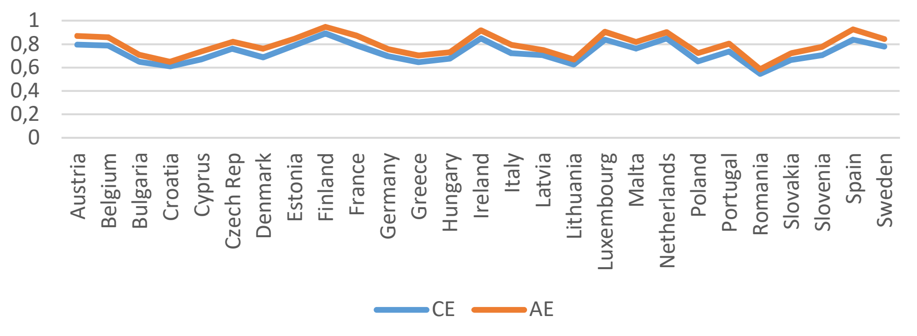
Figure 2 - Cost and allocative efficiencies, with constant returns to scale



Source: Author's calculations.

The values of the cost and allocative efficiencies that were obtained for the whole sample of EU banks are fully in line with those regarding the country-specific efficiencies, which are presented in Figure 2 (considering constant returns to scale) and in Figure 3 (with variable returns to scale). In all situations, the allocative efficiency is higher than the cost efficiency, revealing that the scores of the cost efficiency (representing the combinations of inputs to produce the outputs at minimum costs) are always worse than the scores obtained for the technical and the pure technical efficiencies, which measure how well banks use the inputs to obtain the desired outputs in comparison with the best-achieved performance that is represented by the production possibility frontier.

Figure 3 - Cost and allocative efficiencies, with variable returns to scale



Source: Author's calculations.

4.3. Countries' Ranking Lists

DEA techniques provide the results not only for the whole sample of the considered 784 EU banks but also for the sub-samples of the banks from all EU countries.

Table 2 presents the countries' ranking lists according to the scores obtained for three measures of bank efficiency: technical efficiency, cost efficiency, and allocative efficiency, considering both constant and variable returns to scale. The results do now allow the conclusion that the banks of one specific EU country are always the most efficient because the rankings change according to the different concepts and measures of bank efficiency. Nevertheless, it is still possible to identify some countries (such as Finland, and the Netherlands) that in all situations are in the top positions of the different ranking lists, clearly indicating that their banks look more efficient than the other EU banks included in the sample.

Table 2 - Countries' rankings according to the scores obtained for the EU banking efficiencies

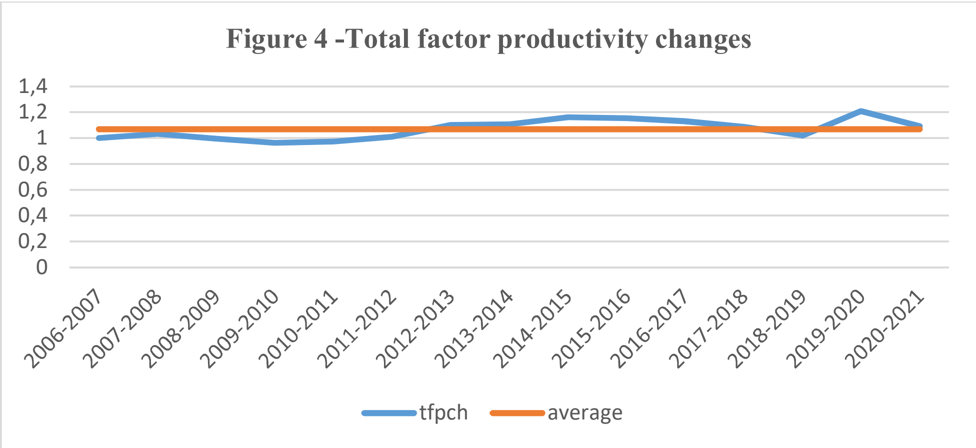
		$\mathbf{TE_{CRS}}$		$\mathbf{CE_{CRS}}$		$\mathbf{AE_{CRS}}$		$\mathbf{TE_{VRS}}$		$\mathbf{CE_{VRS}}$		$\mathbf{AE_{VRS}}$	
1	Latvia	0.934	Finland	0.831	Finland	0.902		Netherlands	0.942	Finland	0.892	Finland	0.946
2	Lithuania	0.922	Spain	0.797	Spain	0.897		Finland	0.941	Ireland	0.85	Spain	0.926
3	Finland	0.919	Estonia	0.756	Estonia	0.841		Latvia	0.94	Netherlands	0.849	Ireland	0.919
4	Malta	0.919	Luxembourg	0.734	France	0.831		Croatia	0.936	Spain	0.839	Luxembourg	0.906
5	Netherlands	0.918	France	0.733	Ireland	0.816		Estonia	0.935	Luxembourg	0.838	Netherlands	0.899
6	Croatia	0.915	Malta	0.733	Luxembourg	0.816		Lithuania	0.935	Austria	0.795	France	0.875
7	Hungary	0.915	Austria	0.72	Austria	0.807		Romania	0.935	Estonia	0.792	Austria	0.872
8	Romania	0.914	Ireland	0.717	Malta	0.797		Czech Rep	0.929	France	0.791	Belgium	0.86
9	Germany	0.911	Czech Rep	0.699	Czech Rep	0.774		Hungary	0.929	Belgium	0.787	Estonia	0.845
10	Slovakia	0.908	Netherlands	0.689	Belgium	0.77		Malta	0.929	Sweden	0.781	Sweden	0.841
11	Bulgaria	0.906	Belgium	0.688	Italy	0.761		Luxembourg	0.927	Czech Rep	0.761	Malta	0.818
12	Luxembourg	0.903	Slovenia	0.686	Slovenia	0.76		Ireland	0.926	Malta	0.761	Czech Rep	0.817
13	Slovenia	0.903	Italy	0.678	Netherlands	0.754		Slovakia	0.924	Portugal	0.737	Portugal	0.804
14	Czech Rep	0.901	Latvia	0.677	Sweden	0.738		Sweden	0.924	Italy	0.722	Italy	0.793
15	Portugal	0.901	Sweden	0.666	Germany	0.731		Germany	0.92	Latvia	0.706	Slovenia	0.777
16	Sweden	0.901	Germany	0.665	Portugal	0.73		Greece	0.92	Slovenia	0.705	Germany	0.76
17	Estonia	0.897	Portugal	0.657	Latvia	0.719		Bulgaria	0.918	Germany	0.699	Denmark	0.757
18	Greece	0.896	Denmark	0.64	Denmark	0.717		Belgium	0.916	Denmark	0.687	Latvia	0.745
19	Cyprus	0.895	Bulgaria	0.637	Cyprus	0.713		Portugal	0.916	Hungary	0.677	Cyprus	0.742
20	Austria	0.894	Cyprus	0.635	Bulgaria	0.705		Austria	0.913	Cyprus	0.671	Hungary	0.727
21	Belgium	0.894	Slovakia	0.626	Poland	0.701		Cyprus	0.909	Slovakia	0.666	Poland	0.726
22	Italy	0.891	Poland	0.62	Slovakia	0.692		Italy	0.909	Poland	0.652	Slovakia	0.723
23	Denmark	0.89	Hungary	0.615	Hungary	0.673		Slovenia	0.908	Bulgaria	0.651	Bulgaria	0.712
24	Spain	0.889	Lithuania	0.597	Lithuania	0.649		France	0.905	Greece	0.647	Greece	0.705
25	Poland	0.886	Croatia	0.577	Greece	0.646		Spain	0.905	Lithuania	0.626	Lithuania	0.672
26	France	0.885	Greece	0.575	Croatia	0.632		Denmark	0.903	Croatia	0.609	Croatia	0.651
27	Ireland	0.88	Romania	0.481	Romania	0.527		Poland	0.9	Romania	0.547	Romania	0.585
	Average	**0.903**	**average**	**0.671**	**average**	**0.744**		**average**	**0.922**	**average**	**0.731**	**Average**	**0.793**

TE=Technical efficiency; CE = Cost efficiency; AE = Allocative efficiency. CRS=Constant returns to scale; VRS = Variable returns to scale.
Source: Author's calculations.

4.4. Malmquist Indices Measuring Technical and Productivity Changes

The values of the computed Malmquist index provide the measures of the annual productivity changes and they allow the decomposition of these changes into the technological changes and the technical efficiency changes. The computed Malmquist index also reports the results of the technical efficiency change (with constant returns to scale), the pure technical efficiency change (with variable returns to scale), the scale efficiency change, and the total factor productivity change. Values greater than one always indicate positive changes between one year and the next one.

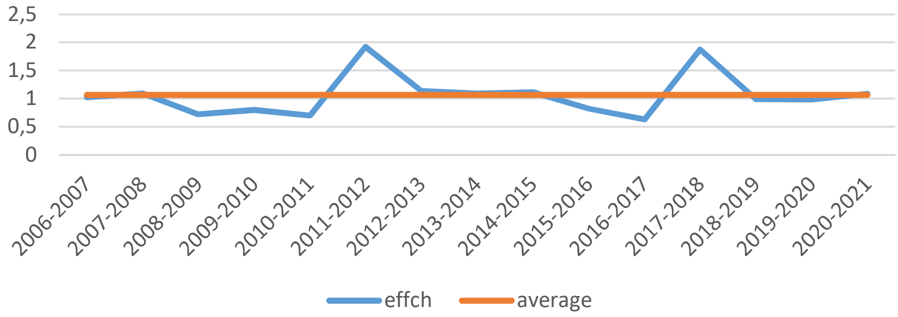
During the considered period the value of total factor productivity changes was, on average, 1.069, and as documented in Figure 4, the year-to-year changes were almost always greater than one, with the exceptions of the years between 2008 and 2011, corresponding to the period of the global financial crisis that deeply affected the EU banking sector.



Source: Author's calculations.

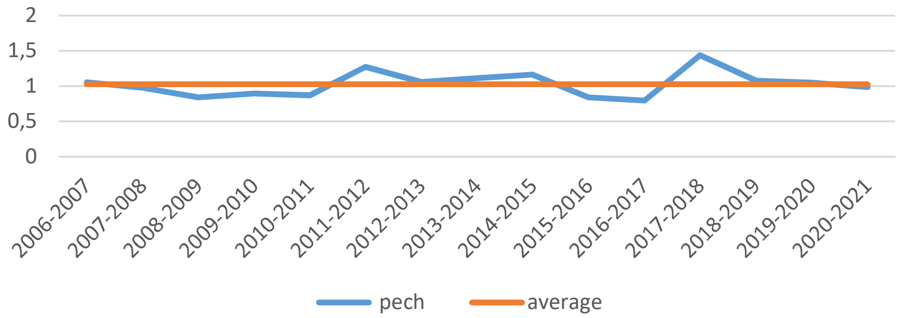
The value of the technical efficiency changes (with constant returns to scale) on average was 1.099, a little higher than the average of the changes of the pure technical efficiency changes (with variable returns to scale), which was 1.029, as well as of the scale efficiency changes, which, on average was 1.014. The next three figures represent the year-to-year evolutions of these efficiency changes. Not surprisingly, the fluctuations of the technical efficiency changes (Figure 5) were a little higher than those of the pure technical changes (Figure 6) and of the scale efficiency changes (Figure 7). The three figures also clearly demonstrate a regress in these efficiency changes during the period of the global financial crisis (2008-2011) as well as between the years 2015-2017 corresponding to a turbulent period of the EU banking sector and the advancements of the European Banking Union with two important initiatives: the European Banking Supervision and the Single Resolution Mechanism.

Figure 5 - Technical efficiency changes, with CRS technology



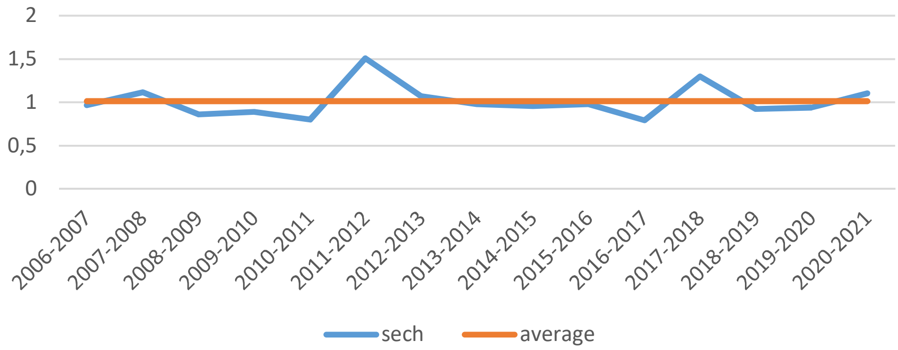
Source: Author's calculations.

Figure 6 -Pure technical efficiency changes, with VRS technology



Source: Author's calculations.

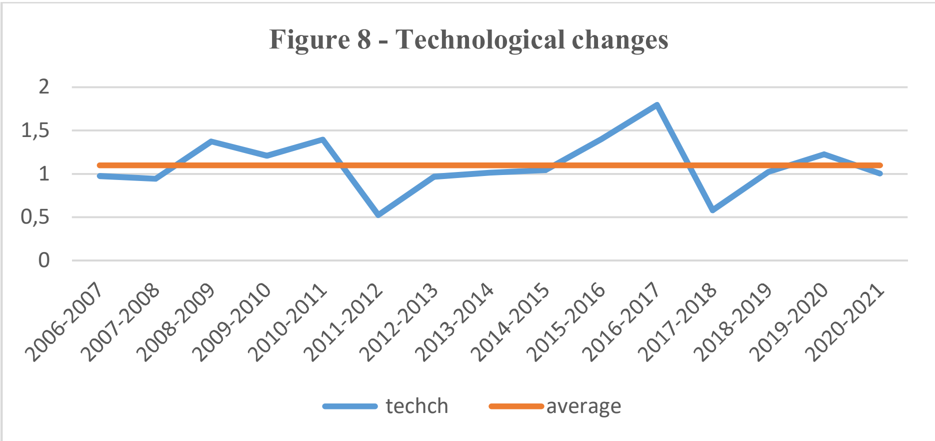
Figure 7 - Scale efficiency changes



Source: Author's calculations.

The results of the computed Malmquist index also provide the measurements of the technological changes. On average, these changes were 1.099, the higher value of all average changes obtained with the Malmquist index computations, clearly indicating technological progress. This progress corresponds to the European Union banks' efficiency shifting out as a result of the adoption of new and more productive technologies by the most efficient banks.

Figure 8 presents the evolution of the technological changes during the considered period, with clear evidence of the strength of the technological progress as a response to the challenges of the global financial crisis and those related to the implementation of the European Banking Union. Not surprisingly, Figure 8 also reveals that after the periods of increased financial progress, there are few years of regress, demonstrating that there are also limits to the introduction of the new technologies adopted by the EU banking institutions.



Source: Author's calculations.

5. **Concluding Remarks**

This paper contributes to the literature on the analysis of the efficiency of the European Union banking sector, considering a panel with 784 relevant banks of all 27 EU countries, between 2006 and 2021. Data Envelopment Analysis techniques are applied to measure different concepts of bank efficiency: technical and pure technical efficiency, scale efficiency, cost efficiency, and allocative efficiency as well as to estimate the different Malmquist indices. Banks are assumed to produce three outputs: loans, other earning assets, and non-earning assets using three inputs: interest expenses, non-interest expenses, and equity.

The results obtained allow the following overall conclusions:

1) On average, the technical efficiency for the whole sample of 784 EU banks during the period 2006-2021 is lower than the pure technical efficiency, showing that the technical inefficiency of the EU banks included in the panel is mainly justified by inefficient managerial performance and non-efficient combinations of the considered inputs and outputs. Moreover, the results obtained for the scale efficiency of the whole sample indicate that overall, the scale of production of the considered EU banks is not very far away from the most productive scale size

2) The results obtained for the cost and the allocative efficiencies, considering both constant and variable returns to scale, clearly indicate that the cost efficiency is much lower than the technical efficiency. More precisely, the allocative efficiency is always higher than the cost efficiency, revealing that the scores of the cost efficiency (representing the combinations of inputs to produce the outputs at minimum costs) are always worse than the scores obtained for the technical and the pure technical efficiencies, which measure how well banks use their inputs to obtain the desired outputs in comparison with the best-achieved performance that is represented by the production possibility frontier.

3) The ranking lists obtained using the results regarding the technical (and pure technical) efficiency, cost efficiency, and allocative efficiency, for the sub-samples of the banks from each EU country do not allow a conclusion that the banks from one specific EU country are always the most efficient. However, it is still possible to conclude that the banks from some EU countries, namely those from Finland and the Netherlands, are in the top positions of the different ranking lists.

4) The values of the computed Malmquist index reveal that

a. The year-to-year changes of the total factor productivity were almost always greater than one, revealing progress, except during the period of the global financial crisis.

b. The year-to-year changes of the technical efficiency were a little higher than those of the pure technical efficiency changes as well as of the scale efficiency changes. Moreover, the values of these three efficiency changes indicate regress not only during the global financial crisis but also between the years 2015-2017, a turbulent period of the EU banking sector with the advancements of the European Banking Union and two relevant initiatives: the European Banking Supervision and the Single Resolution Mechanism.

c. The values of the technological changes also demonstrate that there was significant technological progress, shifting out the EU banks' efficiency with the adoption of new and more productive technologies by the most efficient banks. This progress was a clear response to the challenges of the global financial crisis and those related to the implementation of the European Banking Union. Not surprisingly, the results also demonstrated that after periods of increased financial progress, there are few years of regress, revealing the plausible existence of limits to the adoption of new technologies by the EU banking institutions.

Further research should be encouraged, in this field, namely exploring the bank efficiency measures obtained with the Data Envelopment approach but considering other bank inputs and outputs, with different samples of EU and non-EU banks, during other periods and/or using other methodologies to estimate bank efficiency.

References

Ali, A.I. and Seiford, L.M. (1993) "The Mathematical Programming Approach to Efficiency Analysis" in Fried, H.O., Lovell, C.A.K. and Schmidt, S.S. (Eds), The Measurement of Productive Efficiency, New York, Oxford University Press, pp. 120-159.

Ali, A.I. and Lerme, C.S. (1997) "Comparative advantage and disadvantage in DEA", *Annals of Operations Research*, 73, pp. 215–232. DOI: https://doi.org/10.1023/A:1018929228294

Almanza, C. and Rodríguez, J. J. M. (2018) "Profit efficiency of banks in Colombia with undesirable output: a directional distance function approach", *Economics: the Open-Access, Open-Assessment e-Journal*, journal article no. 2018-30.

Altunbas, Y., Carbo, S., Gardener, E. P. M. and Molyneux, P. (2007) "Examining the Relationships between Capital, Risk and Efficiency in European Banking", *European Financial Management*, 13, pp. 49–70. DOI: 10.1111/j.1468-036X.2006.00285.x

Asmild, M. and Zhu, M. (2016) "Controlling for the use of extreme weights in bank efficiency assessments during the financial crisis", *European Journal of Operational Research*, 251, pp. 999-1015. DOI: https://doi.org/10.1016/j.ejor.2015.12.021

Berg, S. (2010) *Water Utility Benchmarking: Measurement, Methodology, and Performance Incentives*, London and New York, International Water Association. DOI: https://doi.org/10.2166/9781780401690

Candemir, M., Ozcan, M., Gunes, M. and Delikas, E. (2011) "Technical Efficiency and Total Factor Productivity in the Hazelnut Agricultural Sales Cooperatives Unions in Turkey", *Mathematical and Computational Applications*, 16, pp. 66-76. DOI:10.3390/mca16010066

Casu, B. and Molyneux, P. (2003) "A comparative study of efficiency in European banking", *Applied Economics*, 35, pp. 1865-1876. DOI:10.1080/0003684032000158109

Charnes A., Cooper W.W. and Rhodes, E. (1978) "Measuring the Efficiency of Decision-Making Units", *European Journal of Operational Research*, 2, pp. 429 – 444. DOI: https://doi.org/10.1016/0377-2217(78)90138-8

Charnes, A., Cooper W.W., Lewin, A.Y. and Seiford, L.M. (1994) *Data Envelopment Analysis: Theory, Methodology and Application, Boston*, Kluwer Academic Publishers.

Chortareas, G. E., Girardone, C. and Ventouri, A. (2013) "Financial freedom and bank efficiency: Evidence from the European Union," *Journal of Banking & Finance*, 37, pp 1223-1231. DOI: https://doi.org/10.1016/j.jbankfin.2012.11.015

Coelli, T. (1996) *A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program*, CEPA Working Paper 96/08.

Cook, W.D., Tone, K., and Zhu, J. (2014) "Data envelopment analysis: Prior to choosing a model", *Omega*, 44, pp. 1-4. DOI: https://doi.org/10.1016/j.omega.2013.09.004

Cooper, W.W., Seiford, L.M. and Tone, K. (2006) *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*, 2nd Ed., New York, Springer.

Degl'Innocenti, M., Kourtzidis, S. A.,Sevic, Z. and Tzeremes, N. G. (2017) "Investigating bank efficiency in transition economies: A window-based weight assurance region approach", *Economic Modelling*, 67, pp 23-33. DOI: https://doi.org/10.1016/j.econmod.2016.08.015

Drake, L. (2001) "Efficiency and productivity change in UK banking", *Applied Financial Economics*, 11, pp. 557–571. DOI:10.1080/096031001752236825

Favero, C.A. and Papi, L. (1995) "Technical efficiency and scale efficiency in the Italian banking sector: a non-parametric approach", *Applied Economics*, 27, pp. 385-395. DOI: https://doi.org/10.1080/00036849500000123

Fujii, H., Managi, S., Matousek, R. and Rughoo, A. (2018) "Bank efficiency, productivity, and convergence in EU countries: a weighted Russell directional distance model", *The European Journal of Finance*, 24, pp. 135-156. DOI: 10.1080/1351847X.2017.1303527

Huljak, I., Martin, R., and Moccero, D. (2022) "The productivity growth of euro area banks" *Journal of Productivity Analysis*, 58, pp. 15-33. DOI: https://doi.org/10.1007/s11123-022-00637-0

Isaksson, A. (2007) *Determinants of Total Factor Productivity: A Literature Review*, Research and Statistics Branch United Nations Industrial Development Organization (UNIDO), July 2007, available at https://rrojasdatabank.info/87573_determinants_of_total_factor_productivity.pdf

Johnes, J. (2006) "Data envelopment analysis and its application to the measurement of efficiency in higher education", *Economics of Education Review*, 25, pp. 273-288. DOI:10.1016/j.econedurev.2005.02.005

Kocisova, K. (2017) "Measurement of Revenue Efficiency in European Union Countries: A Comparison of Different Approaches", *International Journal of Applied Business and Economic Research*, 15, pp. 31-42.

Kolia, D. L. and Papadopoulos, S. (2022) "Integration in banking efficiency: a comparative analysis of the European Union, the Eurozone, and the United States banks", *Journal of Capital Markets Studies*, 6 (1), pp. 48-70. DOI: 10.1108/JCMS-08-2021-0026

Kuc, M. (2018) *Cost Efficiency of European Cooperative Banks*, Institute of Economic Studies (IES) Working paper 21/2018. Available at https://www.econstor.eu/handle/10419/203199

Kumar, S. and Gulati, R. (2008) "An Examination of Technical, Pure Technical, and Scale Efficiencies in Indian Public Sector Banks using Data Envelopment Analysis", *Eurasian Journal of Business and Economics*, 1, pp. 33-69. Available at https://www.ejbe.org/EJBE2008Vol01No02p33KUMAR-GULATI.pdf

Lovell, C.A.K. (1993) "The Mathematical Programming Approach to Efficiency Analysis" in Fried, H.O., Lovell, C.A.K. and Schmidt, S.S, (Eds), *The Measurement of Productive Efficiency*, New York, Oxford University Press, pp. 3-67.

Lozano-Vivas, A., Kumbhakar, S.C., Fethi, M.D. and Shaban, M. (2011) "Consolidation in the European banking industry: How effective is it?", *Journal of Productivity Analysis*, 36, pp. 247-261. DOIhttps://doi.org/10.1007/s11123-011-0212-8

Ouenniche, J. and Carrales, S. (2018) "Assessing efficiency profiles of UK commercial banks: a DEA analysis with regression-based feedback", *Annals of Operations Research*, 266, pp. 551-587. DOIhttps://doi.org/10.1007/s10479-018-2797-z

San-Jose, L. Retolaza, J. L., and Lamarque, E. (2018) "The Social Efficiency for Sustainability: European Cooperative Banking Analysis", *Sustainability*, 10, pp. 1-21. Available at https://www.mdpi.com/2071-1050/10/9/3271

Tanna, S., Pasiouras, F. and Nnadi, M. (2011) "The effect of board size and composition on the efficiency of UK banks", *International Journal of the Economics of Business*, 18, pp. 441–462. DOI:10.1080/13571516.2011.618617

Vozková, K. and Kuc, M. (2017) "Cost Efficiency of European Cooperative Banks", *International Journal of Economics and Management Engineering*, 11, pp. 2705-2708. Available at file:///C:/Users/candi/Downloads/10008180.pdf

Webb, R. (2003) "Levels of efficiency in UK retail banks: A DEA window analysis", *International Journal of the Economics of Business*, 10, pp. 305–322. DOI:10.1080/1357151032000126256