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

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ABSTRACT: *This paper aims to analyse the evolution of efficiency within a substantial panel of 784 pertinent banks operating across all 27 European Union (EU) member states, covering the period from 2006 to 2021. It further aspires to furnish actionable recommendations for bank managers and policymakers aimed at enhancing the performance and resilience of the EU banking sector. The study employs Data Envelopment Analysis (DEA) techniques, which encompass various concepts and measures of bank efficiency, along with the results provided by the Malmquist index. Banks are assumed to produce three outputs: loans, other earning assets, and non-earning assets, which are generated using three inputs: interest expenses, non-interest expenses, and equity The principal findings reveal the existence of inefficiencies predominantly stemming from suboptimal combinations of inputs and outputs as opposed to scale inefficiencies. The computed values of the Malmquist index exhibit a general trend of progress in efficiency, with notable exceptions observed during the global financial crisis and, to a lesser extent, during the period from 2015 to 2017. The insights gleaned from this study indicate that EU bank managers possess the potential to improve efficiency through more judicious combinations of inputs and cost management strategies. The significance of the banking crisis is reaffirmed as a critical determinant. Furthermore, the paper underscores the pivotal role of policymakers, particularly during the years of 2015 to 2017, which witnessed significant developments within the European Banking Union framework. This research does not substantiate the assertion that banks from any particular EU country maintain a consistent position of superior efficiency, as the rankings exhibit variability depending on the diverse constructs and metrics utilized to gauge bank efficiency. Nonetheless, it is feasible to identify certain countries, such as Finland and the Netherlands, that are consistently positioned among the highest tiers in the various efficiency ranking lists.*

Key Words: *Bank efficiency, Data envelopment analysis, European union banking sector, Malmquist index.*
JEL Classification: *C33 D53 F36 G21.*

1. Introduction

Over the decades, particularly in the aftermath of the last global financial crisis and the subsequent sovereign debt crisis impacting numerous European Union (EU) member states, the EU banking sector has encountered substantial challenges in recalibrating to a transformed economic and financial landscape. The imposition of reformed banking regulations and enhanced supervisory frameworks has necessitated significant adaptive measures among EU banks. In this stringent environment, characterized by historically low interest rates, these institutions have grappled with maintaining profitability.

The efficiency of EU banks is paramount not only for the banking sector itself but also for the overarching economic framework of the EU. This significance is underscored by the fact that banks in Europe continue to serve as the principal sources of credit for both businesses and households. Furthermore, the operational performance of these banks is critical for the effective transmission of monetary policy, ensuring that lending activities are sustained at rates conducive to economic stability.

A substantial corpus of literature has emerged that examines the efficiency of EU banks utilizing frontier methodologies which estimate efficient production frontiers via both parametric and non-parametric

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techniques. Among these approaches, Stochastic Frontier Analysis (SFA), a parametric method grounded in optimization aimed at maximizing profits or minimizing costs, has been prominently utilized, operating under the assumption of a stochastic optimal frontier (see Lozano-Vivas et al., 2011; Vozková & Kuc, 2017; Kuc, 2018; Huljak et al., 2022).

Data Envelopment Analysis (DEA) represents one of the most widely employed non-parametric methodologies for estimating efficient production frontiers. DEA utilizes a linear programming framework adept at measuring the efficiency of distinct decision-making units (DMUs) by incorporating multiple inputs and outputs into the production process. Its application spans both single-country analyses (e.g., Tanna et al., 2011; Ouenniche & Carrales, 2018) and multi-country studies (e.g., Chortareas et al., 2013; San-Jose et al., 2018; Kolia & Papadopoulos, 2022) focused on evaluating the efficiency of European banks.

This paper seeks to contribute to the literature by employing DEA techniques to assess the efficiency of a relatively expansive panel comprising 784 banks across all 27 EU countries from 2006 to 2021. The analysis encompasses various metrics of efficiency, including technical efficiency, pure technical efficiency, scale efficiency, cost efficiency, and allocative efficiency. Additionally, the study utilizes Malmquist indices to quantify temporal changes in efficiency and total productivity.

The computed estimates of technical efficiency (under conditions of constant returns to scale), as well as pure technical efficiency and scale efficiency, suggest that the technical inefficiencies delineated within EU banks predominantly arise from suboptimal combinations of inputs and outputs rather than from issues associated with production scale. Moreover, the findings indicate that allocative efficiency consistently surpasses cost efficiency, revealing that the EU banks within the sampled cohort possess the potential to refine their input combinations to achieve desired output levels at reduced costs.

The analytical framework employed enables the construction of ranking lists categorizing sub-samples of banks from each EU country according to their technical and pure technical efficiency, cost efficiency, and allocative efficiency. Although the data do not yield a conclusive assertion that banks from particular EU countries demonstrate consistent superior efficiency, comparative evaluations of their standings in various ranking lists highlight those institutions that frequently occupy top positions.

Overall, the computed values of the Malmquist index exhibit a general progression, save for the period corresponding to the global financial crisis and, to a lesser extent, between 2015 and 2017—a turbulent interval for the EU banking sector coinciding with the advancements of the European Banking Union, European Banking Supervision, and the Single Resolution Mechanism initiatives.

The structure of this paper is delineated as follows: Section 2 presents a comprehensive review of the pertinent literature; Section 3 elucidates the methodology and data employed; Section 4 discusses the obtained results; and Section 5 encapsulates the conclusions derived from the analysis.

2. Relevant Literature

The existing body of literature on bank efficiency predominantly investigates the potential to delineate an efficiency frontier that represents the optimal amalgamation of requisite inputs to achieve desired outputs. The efficiency of a financial institution, therefore, is conceptualized as its deviation from this defined efficiency frontier, which can be ascertained through both parametric and non-parametric methodologies.

One of the preeminent non-parametric approaches employed in this domain is Data Envelopment Analysis (DEA), initially introduced by Charnes et al. (1978) and further advanced by scholars such as Ali & Seiford (1993), Lovell (1993), Cooper et al. (2006), and Cook et al. (2014). DEA utilizes a linear programming framework to measure the efficiency of various decision-making units (DMUs) characterized by multiple inputs and outputs within their production processes. This methodology has frequently been applied to evaluate and compare the efficiency performance of banking institutions across different countries or regions, particularly within the context of European banking entities, encompassing both focused studies and multi-national analyses.

For instance, Favero & Papi (1995) conducted a study utilizing non-parametric DEA to assess the technical and scale efficiencies of 174 Italian banks in 1991. Their findings indicated the presence of both technical and allocative efficiencies, with regression analysis revealing that bank efficiency was most significantly influenced by factors such as productive specialization, size, and, to a lesser extent, geographical location.

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Similarly, Drake (2001) examined relative efficiencies and productivity changes among major UK banks from 1984 to 1995, yielding valuable insights into the size-efficiency relationship within the sampled banks and shedding light on the evolving structural and competitive dynamics in which these institutions operate. Webb (2003) employed DEA window analysis to measure the relative efficiency levels of large UK retail banks from 1982 to 1995, discovering a declining trend in overall long-run average efficiency and consistent reductions in efficiency across all banks within the study's scope.

Tanna et al. (2011) analysed a sample of 17 banking institutions in the UK between 2001 and 2006, utilizing DEA techniques to investigate the relationship between bank efficiency and board structure, particularly board size and composition. Their results provided evidence of a positive association between board size and efficiency, as well as compelling evidence that board composition significantly and positively affected various efficiency measures.

Ouenniche & Carrales (2018) further examined the efficiency profiles of UK banks by collecting data from 109 commercial banks spanning the years 1987 to 2015. Their findings indicated that, on average, commercial banks in the UK had yet to attain satisfactory levels of overall technical efficiency, pure technical efficiency, and scale efficiency.

Looking beyond individual countries, multi-country DEA studies have also been instrumental in analysing the efficiency of European banks. For example, Casu & Molyneux (2003) assessed a sample of 750 banks from five EU countries—namely France, Germany, Italy, Spain, and the UK—aiming to explore the potential for improvement and convergence in efficiency following the establishment of the Single Internal Market. Their results suggested modest improvements in bank efficiency levels; however, they found no compelling evidence supporting the notion of convergence in productive efficiency among EU banks.

Chortareas et al. (2013) utilized a substantial sample of commercial banks from 27 EU member states throughout the 2000s, employing data from the Bankscope database to estimate bank-specific efficiency scores via DEA. This study investigated the interplay between the efficiency levels of banks and the financial freedom indicators derived from the economic freedom index published by the Heritage Foundation. The findings indicated that a higher degree of financial freedom within a country corresponded with enhanced cost advantages and overall efficiency for banks operating within that jurisdiction.

Degl'Innocenti et al. (2017) employed a two-stage Data Envelopment Analysis (DEA) model to evaluate the efficiency of 116 banks across nine Central and Eastern European (CEE) countries that are EU members, spanning the period from 2004 to 2015. In the initial stage, total assets and personnel expenses were designated as inputs, while deposits were identified as outputs of the "value-added activity." Subsequently, in the second stage, deposits were reclassified as inputs for the "profitability activity," where loans and securities emerged as the ultimate outputs. The findings from this study indicated a persistently low level of efficiency throughout the analysis period, particularly pronounced within Eastern European and Balkan nations. Furthermore, the authors concluded that the inefficiencies observed within CEE countries were predominantly attributable to the profitability stage, rather than the value-added activity stage.

Asmild & Zhu (2016) examined the intersection of risk and efficiency among European banks, utilizing a sample of 71 banks from 20 distinct EU member states during the years 2006 to 2009, with data sourced directly from each bank's audited financial statements. To investigate the ramifications of proposed weight restrictions, the authors developed two DEA models: the “Funding Mix Model,” which incorporated five inputs (retail funding expenses, wholesale funding expenses, physical capital expenses, personnel expenses, and impaired loans) and two outputs (loans and financial assets), and the “Asset Mix Model,” which also utilized five inputs (property loans, non-property loans, trading financial assets, non-trading financial assets, and impaired loans) alongside two outputs (income and provisions for impaired loan losses). The results indicated that a more balanced set of weights generally led to a reduction in estimated efficiency scores, particularly among those banks that received bailouts during the financial crisis. This finding underscored potential biases and limitations inherent in DEA estimations, revealing that the decreases in efficiency scores following weight restrictions were substantially more pronounced for bailed-out banks compared to their non-bailed-out counterparts.

Kocisova (2017) conducted DEA estimations to assess the efficiency of the banking sectors across EU countries in 2015, utilizing data compiled from the European Central Bank’s database. The results derived from DEA estimations suggested that larger banking sectors exhibited the highest levels of efficiency. This study emphasized the advantages of employing DEA, as it provides insights on how banks might optimize

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their input and output structures, considering output prices, thereby facilitating a shift toward the efficiency frontier. However, the paper also elucidated some limitations of the DEA methodology, noting that it calculates relative efficiency within a selected group of decision-making units (DMUs) and specific variables (inputs, outputs, and output prices). Consequently, alterations in the group of DMUs or the chosen variables could result in shifts in both the efficiency frontier and the efficiency levels assigned to each DMU.

San-Jose et al. (2018) investigated the nexus between economic efficiency and sustainability within the European banking sector, applying DEA methodologies to a comprehensive sample of 2,752 financial institutions—differentiating among commercial, cooperative, and savings banks—from the EU-15 countries in 2014. Their principal findings revealed a lack of harmonization within European banking and provided evidence suggesting that no trade-off existed between social efficiency and economic efficiency. Additionally, this research contributed to the ongoing discourse regarding the strengths and weaknesses of the DEA approach, highlighting its exceptional flexibility due to the absence of pre-established relationships between inputs and outputs. This characteristic enables a quasi-realistic representation of the interrelationship among variables. Nonetheless, the study also pointed out that DEA represents a deterministic method that assumes that if one DMU achieves a certain output level with a given input, other DMUs should be able to reach the same level. Moreover, the choice of variables is critically important, as there are no robust tests available to ascertain whether the analysis results are stable or would vary considerably with alternative variables.

Kolia & Papadopoulos (2022) explored the evolution of bank efficiency and the progression of banking integration from 2013 to 2018, assessing whether banking integration within Euro area countries advanced more significantly than the cumulative integration of the broader European landscape. Furthermore, they compared the developments in efficiency and integration across Euro area countries with that of the United States. Bank efficiency was measured using DEA estimations, which included three inputs (labour, capital, and deposits) and two outputs (loans and net interest income). The findings indicated that the efficiency of the U.S. banking system substantially exceeded that of banks within the Euro area and the EU at large. Overall, the study concluded that there was no compelling evidence of convergence across the banking groups analysed.

3. Methodology and Data

The present article employs Data Envelopment Analysis (DEA), a robust non-parametric methodology for assessing the relative efficiency of various decision-making units (DMUs) through the utilization of multiple inputs and outputs in a production context. Acknowledging that the outcomes derived from this methodology are particularly responsive to the selection of inputs and outputs, as well as the propensity for the number of efficient DMUs to escalate with the incorporation of additional variables, DEA nonetheless remains a valid choice for evaluating efficiency, including that of banking institutions.

In comparison to other established methodologies, DEA offers several distinct advantages: it accommodates multiple inputs and outputs without necessitating an explicit definition of a production function; it is applicable across diverse input-output measurements; and it enables the derivation of efficiency (as well as inefficiency) metrics for each DMU under consideration.

The DEA framework is principally grounded in a linear programming paradigm, initially articulated by Charnes et al. (1978) and subsequently refined by scholars such as Ali & Seiford (1993), Lovell (1993), Charnes et al. (1994), and Cooper et al. (2006). Today, DEA is recognized as a well-established non-parametric efficiency technique that is well-suited for the analysis of various DMUs by leveraging multiple inputs and outputs in production processes.

The foundational model proposed by Charnes et al. (1978) operates under the assumption of constant returns to scale and is thoroughly elucidated in Coelli (1996). In this model, it is assumed that each of the N firms (or DMUs) utilizes K inputs to generate M outputs, characterized by the KxN input matrix (X) and the MxN output matrix (Y), which collectively encapsulate the data for all N DMUs. By applying linear programming, one methodology for gauging efficiency involves solving the following optimization problem:

$$Min_{\theta,\lambda}\ \theta,$$
$$\text{Subject to:} \quad -y_i + Y\lambda \geq 0; \quad \theta y_i - X\lambda \geq 0; \quad \lambda \geq 0 \qquad (1)$$

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

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Solving this problem, we obtain, for each DMU, the efficiency score θ. In all situations $\theta \leq 1$; when $\theta = 1$ the respective DMU resides on the efficient frontier, indicating optimal performance relative to its peers. Conversely, when they are not in the frontier the values of $1 - \theta$ reflect the distance of the DMU from the efficient frontier, serving as a metric for their technical inefficiencies.
Under the specified conditions, the technical efficiency of each DMU serves as a comparative metric for evaluating the efficacy with which inputs are transformed into desired outputs, relative to the optimal performance delineated by the production possibility frontier. This comprehensive measure of efficiency is contingent not only upon the specific input/output combinations (representing the pure technical efficiency) but also on the scale of the production operation (or the scale efficiency).
Still following Coelli (1996), we may incorporate the assumption of variable returns to scale, including the convexity constraint represented by $N1'\lambda = 1$ in the formulation of model (1). Subsequently, we can resolve the ensuing linear programming problem to derive a quantitative measure of pure technical efficiency:

$$Min_{\theta,\lambda}\ \theta,$$
$$\text{Subject to:} \quad -y_i + Y\lambda \geq 0; \quad \theta y_i - X\lambda \geq 0; \quad N1'\lambda = 1; \quad \lambda \geq 0 \qquad (2)$$

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

Assuming the presence of variable returns to scale, the measurement of pure technical efficiency fundamentally serves as an indicator of managerial performance. Conversely, scale efficiency reflects management's capability to determine the optimal scale of production and can be quantitatively derived as the ratio of overall technical efficiency—assumed under constant returns to scale—to pure technical efficiency (see, among others, Kumar & Gulati, 2008; Fujii et al., 2018).

To derive allocative efficiency, it is necessary to first obtain the measure of cost efficiency by solving the following optimisation problem:

$$Min_{\lambda, x_i^*}\ w_i'x_i^*,$$
$$\text{Subject to:} \quad -y_i + Y\lambda \geq 0; \quad x_i^* - X\lambda \geq 0; \quad N1'\lambda = 1; \quad \lambda \geq 0 \qquad \mathbf{(3)}$$

(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).

To address this problem, one can derive 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 determined by the ratio of the cost efficiency (CE) to the technical efficiency (TE), that is AE=CE/TE.

In the context of panel data analysis, it is possible to employ a Data Envelopment Analysis (DEA) linear programming framework to derive the Malmquist index. This index serves to quantify changes in productivity, allowing for a decomposition into two principal components: technical change and technical efficiency change. As discussed in the literature, including the work of Candemir et al. (2011), the Malmquist productivity change index for the interval between time period t and time period t+1 can be defined as follows:

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

This index can be decomposed into the

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

and the

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

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The DEA methodology is widely acknowledged as a robust approach for the evaluation and measurement of efficiency across various sectors, including the banking industry. Among its notable advantages, DEA accommodates multiple inputs and outputs without necessitating a predefined production function, thereby allowing for versatile applicability across diverse input-output frameworks. Furthermore, DEA is capable of generating efficiency and inefficiency assessments for each DMU under consideration.

However, DEA is not without its limitations. A significant drawback is the inability to conduct tests for superior model specifications, which can undermine the validity of results obtained. Additionally, DEA's findings exhibit considerable sensitivity to the selected inputs and outputs; for example, the number of efficient DMUs tends to increase as more input and output variables are incorporated into the analysis (as well documented, for instance in Ali & Lerme, 1997; Johnes, 2006; Berg, 2010).

In this paper, we assume that banks are DMU producing three outputs: loans, other earning assets, and non-earning assets, using three inputs: interest expenses, non-interest expenses, and equity. The inclusion of equity serves to account for the influence of risk preferences on efficiency estimations, as noted in the literature (see, for example, Altunbas et al., 2007; Almanza & Rodríguez, 2018).

To evaluate cost efficiency, it is necessary to acquire information pertaining to production costs. In this analysis, costs are proxied in these ways: first, by the ratio of interest expenses to deposits and short-term funding, which serves as a metric for the cost of borrowed funds; second, by the ratio of non-interest expenses to total assets, representing the price of capital and labour; and third, by the ratio of equity to total assets, which is indicative of the cost associated with equity.

Under these assumptions, the objective is to identify the optimal combination of inputs to produce outputs at the lowest possible cost. According to the established methodology, allocative efficiency (AE) is defined as the ratio of cost efficiency (CE) to technical efficiency (TE). This analysis allows for the consideration of either constant returns to scale (CCR) or variable returns to scale (VRS).

The data utilised for this study regarding the selected bank outputs, inputs, and production costs were obtained from the Moody's Analytics BankFocus database as of December 2022. The paper examines a comprehensive panel of 784 banks across all 27 member states of the European Union (EU) over the period from 2006 to 2021. The selection criteria for these banks not only factored in data availability but also considered the size of the institutions, given the potential impact of bank size on banks' behaviour. Consequently, banks with total assets of less than 2 billion Euros in 2021 were excluded from the sample. Nonetheless, in instances where certain EU countries exhibited a scarcity of banks with significant total assets, banks with total assets approaching but not exceeding 1 billion Euros in 2021 were incorporated into the analysis.

Table 1 provides information about the number of banks from each of the 27 EU countries included in the sample, alongside their representativeness in terms of the proportion of the total number of banks, total deposits, and total loans extended to customers within the broader sample.

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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

This section begins by reporting the technical efficiency of banks in each EU country, distinguishing between constant returns to scale and pure technical efficiency with variable returns to scale. It then analyses scale efficiency over the evaluated period.

Next, the paper presents the values for cost and allocative efficiencies under both constant and variable returns to scale.

In the third step, the paper ranks the countries based on the scores obtained for the three efficiency measures: technical, cost, and allocative efficiencies, considering both constant and variable returns to scale.

Finally, the paper provides the results of the computed Malmquist indices, which measure changes in technical, technological, and scale efficiency, as well as overall productivity changes.

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

The measurement of technical efficiency, utilizing the constant returns to scale approach, for the comprehensive sample of 784 European Union banks over the period from 2006 to 2021, yields a technical efficiency score (TE_{CRS}) of 0.903. In contrast, the assessment of pure technical efficiency, employing the variable returns to scale methodology, yields a score (TE_{VRS}) of 0.922. These findings suggest that the

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observed technical inefficiency within the European banks under study predominantly arises from suboptimal managerial performance and inefficient configurations of the inputs and outputs examined.

Furthermore, the calculation of scale efficiency, which reflects the managerial ability to select the optimal scale of production, is derived from the ratio of TE_{CRS} to TE_{VRS}. For the entire sample, the scale efficiency is determined to be 0.980, indicating that the scale of production employed by the EU banks is generally aligned with the most productive scale size.

Figure 1 illustrates the results pertaining to technical efficiency, pure technical efficiency, and scale efficiency for the designated banks across all EU member states throughout the period of analysis from 2006 to 2021. Consistent with the findings for the aggregate sample of EU banks, there is robust evidence to suggest that the scale of bank production is largely appropriate, and the efficiency of banks is consistently higher when evaluated under the framework of variable returns to scale.

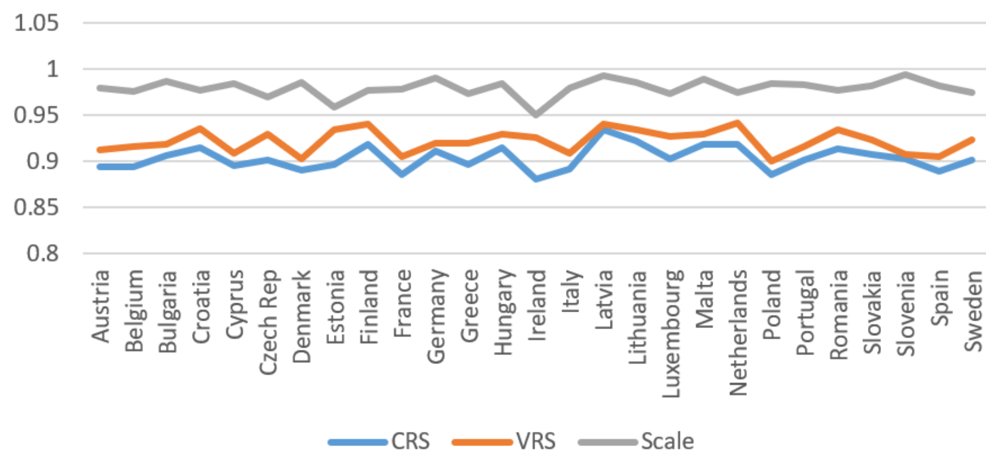

Figure 1. Technical efficiency (with CRS), pure technical efficiency (with VRS) and scale efficiency.

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

As previously explained, cost efficiency encompasses the judicious selection of requisite inputs, taking into account their associated costs. More specifically, it pertains to the identification of optimal combinations of inputs to facilitate the production of outputs at minimum expenditure. Adhering to the methodology delineated in the preceding section, allocative efficiency (AE) is defined as the ratio of cost efficiency (CE) to technical efficiency (TE), applicable under both constant and variable returns to scale.

In the context of constant returns to scale, the analysis of a comprehensive sample comprising 784 EU banks over the period from 2006 to 2021 yields a cost efficiency (CE_{CRS}) of 0.671 and an allocative efficiency (AE_{CRS}) of 0.744.

Conversely, when evaluating variable returns to scale, the findings indicate a cost efficiency (CE_{VRS}) of 0.731 and an allocative efficiency (AE_{VRS}) of 0.793. These results substantiate the assertion that bank efficiency is significantly enhanced when the scale of bank production is not held constant. Furthermore, the analysis reveals that cost efficiency is markedly inferior to technical efficiency, thereby indicating a notable presence of allocative inefficiency—signifying the challenges faced by EU banks in effectively directing funding towards the most productive applications.

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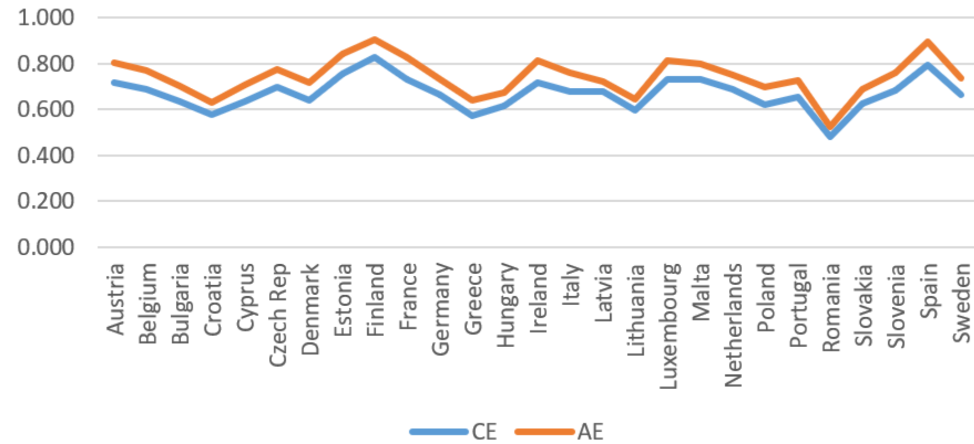

Figure 2. Cost and allocative efficiencies, with constant returns to scale.

The values associated with cost and allocative efficiencies assessed for the entire sample of EU banks are consistent with the country-specific efficiencies delineated in Figure 2 (which accounts for constant returns to scale) and Figure 3 (which incorporates variable returns to scale). In all situations, allocative efficiency consistently surpasses cost efficiency. This indicates that the cost efficiency scores—reflecting the optimal combinations of inputs to generate outputs while minimizing costs—are consistently inferior to the scores derived from both technical and pure technical efficiencies. The latter metrics evaluate the effectiveness with which banks utilize inputs to achieve the intended outputs, in comparison to the optimal performance represented by the production possibility frontier.

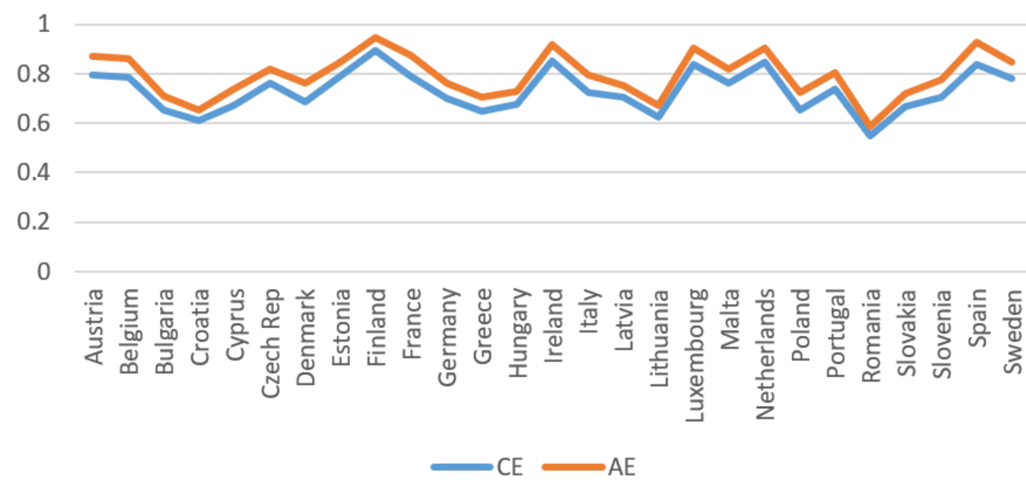

Figure 3. Cost and allocative efficiencies, with variable returns to scale.

4.3. Countries' Ranking Lists

Data Envelopment Analysis (DEA) techniques yield insights not only regarding the entire sample of 784 EU banks but also for individual sub-samples derived from each EU member state.

Table 2 delineates the rankings of countries based on scores from three distinct measures of bank efficiency: technical efficiency, cost efficiency, and allocative efficiency, while accounting for both constant and variable returns to scale.

The findings suggest that no single EU country's banks consistently rank as the most efficient across all measures; rather, the rankings fluctuate depending on the specific efficiency criterion applied. Nevertheless, certain countries, notably Finland and the Netherlands, consistently occupy top positions across the various ranking lists. This observation underscores the relative efficiency of banks in these nations compared to their EU counterparts within the analysed sample.

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

		TE_{CRS}		**CE_{CRS}**		**AE_{CRS}**	**TE_{VRS}**		**CE_{VRS}**		**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

Note: TE=Technical efficiency; CE = Cost efficiency; AE = Allocative efficiency. CRS=Constant returns to scale; VRS = Variable returns to scale.

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4.4. Malmquist Indices Measuring Technical and Productivity Changes

The computed Malmquist index serves as a metric for assessing annual productivity changes, facilitating the decomposition of these transformations into components of technological change and technical efficiency change. Specifically, the Malmquist index delineates results pertaining to technical efficiency change (assuming constant returns to scale), pure technical efficiency change (under variable returns to scale), scale efficiency change, and total factor productivity change. Values exceeding one consistently signify positive alterations from one year to the subsequent year.

Throughout the analysed period, the mean value of total factor productivity changes was approximately 1.069. As illustrated in Figure 4, the year-on-year changes predominantly exceeded one, with the notable exceptions occurring between 2008 and 2011. This interval corresponds to the global financial crisis, which profoundly impacted the European Union banking sector, resulting in a temporary decline in productivity advancements.

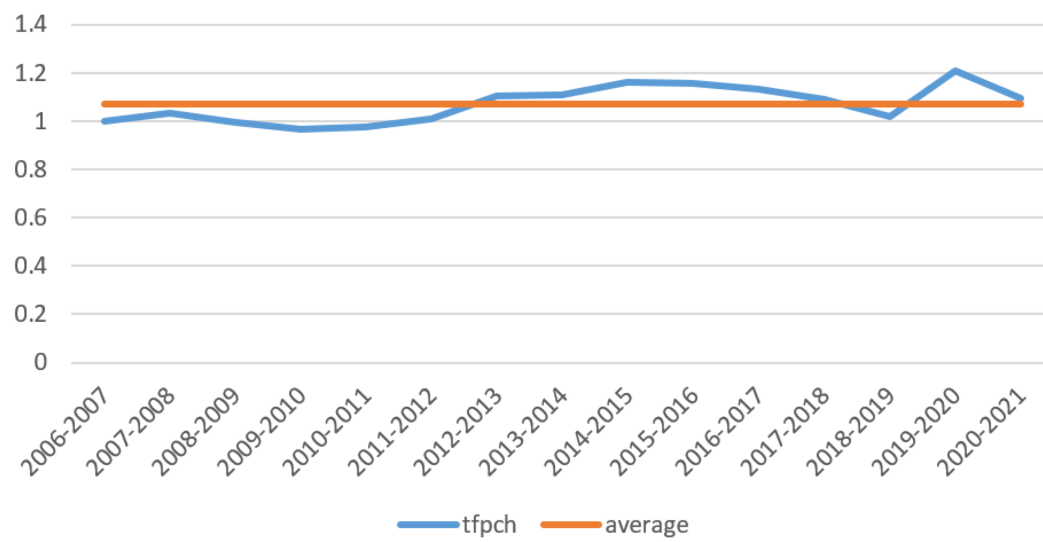

Figure 4. Total factor productivity changes.

The average value of the technical efficiency changes, assuming constant returns to scale, was calculated at 1.099. This figure slightly exceeds the average of the pure technical efficiency changes, which was 1.029 under variable returns to scale, as well as the average scale efficiency changes, which stood at 1.014.

The subsequent figures illustrate the year-on-year developments of these efficiency changes. Notably, the fluctuations observed in the technical efficiency changes (depicted in Figure 5) were marginally greater than those in the pure technical efficiency changes (illustrated in Figure 6) and the scale efficiency changes (shown in Figure 7).

Furthermore, these figures distinctly highlight a regression in efficiency changes during the period of the global financial crisis from 2008 to 2011, as well as during the years 2015 to 2017, a timeframe characterized by significant volatility in the EU banking sector and the progress of the European Banking Union, marked by two pivotal initiatives: the establishment of European Banking Supervision and the implementation of the Single Resolution Mechanism.

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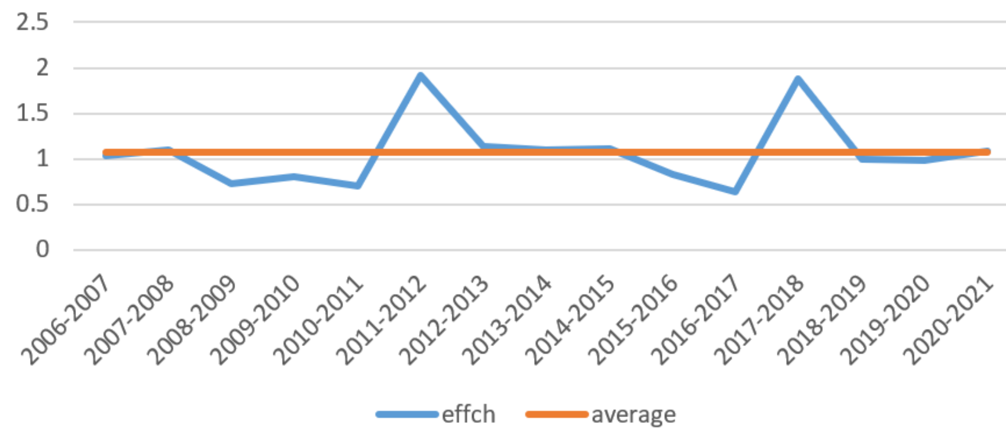

Figure 5. Technical efficiency changes, with CRS technology.

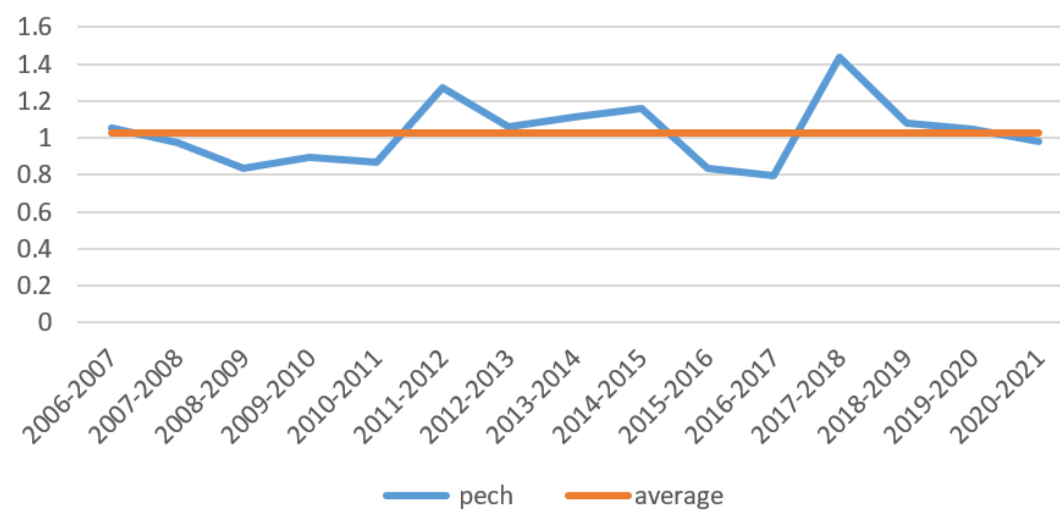

Figure 6. Pure technical efficiency changes, with VRS technology.

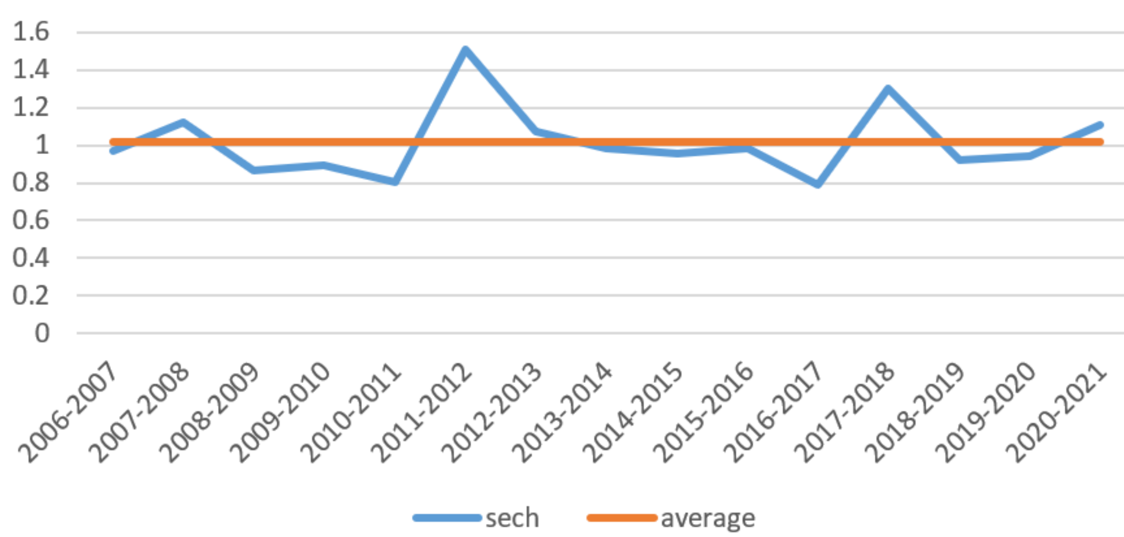

Figure 7. Scale efficiency changes.

The findings derived from the computed Malmquist index offer significant insights into the measurements of technological change within the banking sector. The average technological change was quantified at 1.099, representing the highest value recorded among all average changes obtained through Malmquist index

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computations. This notably underscores the presence of technological advancement within this domain. Such progress is attributed to the efficiency of European Union banks, which has notably improved due to the adoption of novel and more productive technologies by the most efficient banks in the sector.

Figure 8 illustrates the temporal evolution of technological change during the analysed period, providing compelling evidence of the robust technological progress that has emerged in response to the challenges posed by the global financial crisis and the initiatives associated with the implementation of the European Banking Union. Moreover, it is worth noting that Figure 8 highlights that subsequent to periods characterized by heightened financial progress, there exist intervals marked by regression. This observation underscores the notion that there are still limitations to the integration and effectiveness of new technologies embraced by banking institutions within the European Union.

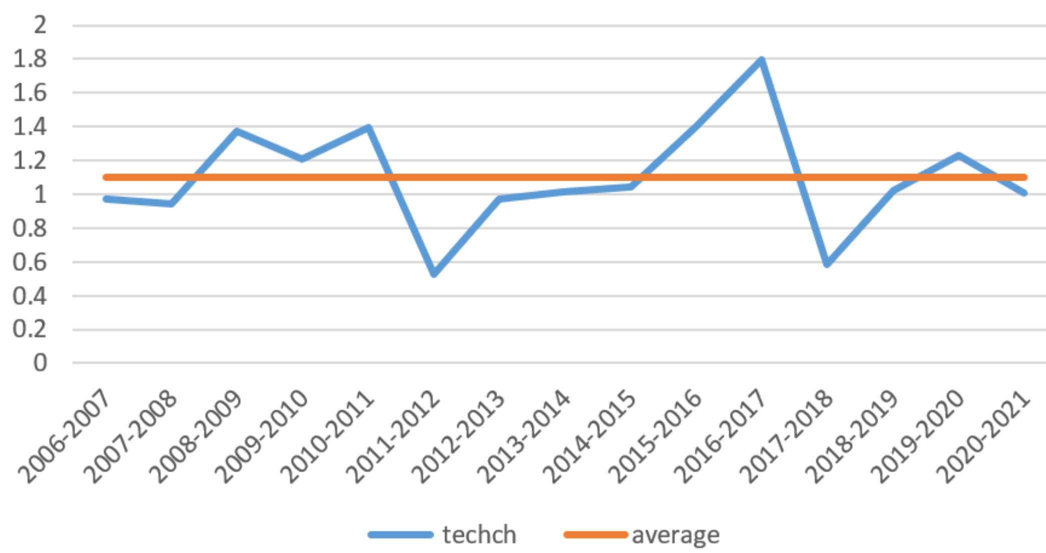

Figure 8. Technological changes.

5. Concluding Remarks

This paper provides a significant contribution to the existing literature on the efficiency analysis of the European Union banking sector by examining a comprehensive panel consisting of 784 banks across all 27 EU member states for the period spanning from 2006 to 2021. Employing Data Envelopment Analysis (DEA) techniques, the study measures various dimensions of bank efficiency, including technical efficiency, pure technical efficiency, scale efficiency, cost efficiency, and allocative efficiency, in addition to estimating various Malmquist indices. In the analysis, banks are conceptualized as producing three distinct outputs: loans, other earning assets, and non-earning assets, utilising three primary inputs: interest expenses, non-interest expenses, and equity.

The findings yield several pertinent conclusions:

1) The average technical efficiency observed within the entire sample of 784 EU banks during the designated timeframe is found to be lower than the pure technical efficiency. This disparity suggests that the technical inefficiencies identified among the banks in the panel are predominantly attributable to suboptimal managerial performance and inefficient combinations of the specified inputs and outputs. Furthermore, the results concerning scale efficiency reveal that the overall production scale of the banks under consideration is relatively close to the most productive scale size.
2) The results pertaining to cost efficiency and allocative efficiency—considering both constant and variable returns to scale—clearly demonstrate that cost efficiency is significantly lower than technical efficiency. Notably, allocative efficiency consistently exceeds cost efficiency, indicating that the scores reflecting cost efficiency (which represent the optimal combinations of inputs required to produce outputs at minimal costs) are consistently inferior to those obtained for both technical and pure technical efficiencies. These latter measures evaluate the efficacy with which banks utilise their inputs to achieve desired outputs in comparison to the best-performing institutions, as represented by the production possibility frontier.

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3) The ranking lists derived from the analyses of technical efficiency, pure technical efficiency, cost efficiency, and allocative efficiency for the subsets of banks from each EU member state do not permit a definitive conclusion regarding the superior efficiency of banks from any particular EU country. However, it is evident that banks from certain EU countries, notably Finland and the Netherlands, consistently occupy the leading positions across various ranking lists.

4) The values of the computed Malmquist index indicate that

a. The year-on-year changes in total factor productivity were predominantly greater than one, suggesting overall progress, with the notable exception of the period encompassing the global financial crisis.

b. The annual shifts in technical efficiency exceeded those of pure technical efficiency and scale efficiency changes. The findings reveal regressions not only during the global financial crisis but also throughout the period from 2015 to 2017. This turbulent phase for the EU banking sector coincided with significant advancements in the European Banking Union, particularly through the introduction of the European Banking Supervision and the Single Resolution Mechanism.

c. The values reflecting technological change illustrate a marked progression in technology, evidenced by the adoption of innovative and more productive technologies by the most efficient banks within the EU. This technological advancement can be interpreted as a direct response to both the challenges posed by the global financial crisis and the subsequent implementation of the European Banking Union. It is noteworthy that the results also indicate that after phases of notable financial progress, subsequent years have experienced regressions, implying the potential existence of limitations to the adoption of new technologies by EU banking institutions.

Future research should be encouraged, in this domain, particularly with respect to examining bank efficiency measures derived from the Data Envelopment Analysis framework. This exploration would, for example, consider alternative inputs and outputs for banks, involve diverse samples of both EU and non-EU banks, encompass different time periods, and/or employ different methodologies for estimating bank efficiency.

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References

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

Ali, A.I. & 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. & 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. & 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. & 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. & 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. & 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. & 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. & Seiford, L.M. (1994) *Data Envelopment Analysis: Theory, Methodology and Application, Boston*, Kluwer Academic Publishers.

Chortareas, G. E., Girardone, C. & 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.

International Journal of Business Management and Finance Research
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2025
DOI: *10.53935/26415313.v8i3.399*
Email: candidaf@iseg.ulisboa.pt

Cook, W.D., Tone, K., & 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. & 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. & 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. & 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. & 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., & 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. & 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. & 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. & 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. & 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. & 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., & 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. & 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. & 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

International Journal of Business Management and Finance Research
Vol. 8, No. 3, pp. 12-26
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DOI: *10.53935/26415313.v8i3.399*
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