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Key factors of European banking efficiency: an application of DEA methodology

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Abstract

Purpose – The banking sector is one of the main drivers of any developed economy and the decisions of individual banks can have global consequences on markets. In recent decades, the European banking sector has undergone major transformations, including restructuring, mergers and changes in regulation and supervision. This has attracted the interest of academics and policymakers alike. The purpose of this paper is to analyze the efficiency in the European banking sector, but there is no consensus in the literature on which factors of banks affect their efficiency.

Design/methodology/approach – This study analyzes data from the consolidated financial statements of a sample of 471 banks over the period 2005–2022 from 39 countries. Two methodologies are applied: data envelopment analysis methodology for the calculation of efficiency, both input- and output-oriented, and Tobit regression model to determine which variables significantly affect banks' efficiency scores.

Findings – The results show that the efficiency scores are similar in the input-oriented and output-oriented model. The Tobit model shows that the variables that positively affect efficiency are the ROA, size, capital ratio and liquidity. On the other hand, the variables that decrease the extent of efficiency are the provisions ratio and the fact of being a financial entity under the Single Supervisory Mechanism.

Originality/value – The main contribution of this study is a more comprehensive and global approach that includes aspects of the most important insights from the previous literature, over a very extended period and including bank and macroeconomic environment characteristics.

Keywords DEA methodology, BCC model, Tobit model, Efficiency, Banking sector

Paper type Research paper

1. Introduction

The efficiency has been measured since the earlier studies by Farrell (1957) by comparing the input necessary to obtain a certain output. A few years later, Charnes *et al.* (1978) introduced the data envelopment analysis (DEA), a tool for measuring efficiency and productivity of decision-making units. The DEA is a methodology based on mathematical programming to obtain optimal

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relationships between a group of inputs and a group of outputs (Bhatia *et al.*, 2018; Ji and Lee, 2010; Lita and Stamule, 2018). Since then, there has been a proliferation of publications on the DEA (Emrouznejad and Yang, 2018). During all this time, theoretical procedures and practical applications of this tool have been developed, giving rise to other variants, such as the model proposed by Banker *et al.* (1984), known as the Banker-Charnes-Cooper (BCC) model.

DEA is used to measure efficiency in different productive sectors located in different countries around the world. In our study, we have applied this methodology to the banking sector, due to the relevant role it performs in every developed economy (Tarasenko *et al.*, 2022), being even one of the most notable indicators that has been used to define the different economic situations that have occurred in recent years. Also, Gazi *et al.* (2021) explain that the stability of a country and the economic growth depends on the soundness of its banking sector. Hence, the special peculiarity of the banking sector, compared to others, is that its activity affects both the economy and the financial stability of a region. Moreover, although efficiency has been analyzed previously in banking literature, the application of the DEA methodology is a contribution of this study. This methodology has been claimed to be more appropriate than other methodologies such as traditional regression models, being a more robust methodology in handling extreme values and outliers (Aigner *et al.*, 1977; Wilson, 2008). This fact is advantageous in real-world applications where data may contain outliers or be noisy (Wilson, 2008). In addition, in sectors where the form of the relationship between the outputs and the necessary inputs to obtain them is not clear, DEA as a nonparametric technique that does not require strong distributional assumptions, overcomes other traditional parametric ones (Aigner *et al.*, 1977; Fare *et al.*, 1985; Seiford and Zhu, 1999; Simar and Wilson, 2007). Finally, the possibility of combining estimation of efficiency in complex environments with multiple inputs and outputs (Charnes *et al.*, 1978; Seiford and Zhu, 1999) with other statistical analysis, such as the Tobit regression, allows for a better understanding of the efficiency determinants (Coelli *et al.*, 2005; Simar and Wilson, 2007). This study, hence, applicates DEA methodology to analyze efficiency determinants in the banking sector in a wider period of study, englobing several economic cycles and geographical settings, contributing for a deeper understanding of banking efficiency and offering a guidance on tips to be considered by the banking sector practitioners and regulators.

Specifically, our paper focuses on the European banking sector, which despite the intrinsic characteristics of the institutions in each country, over time, its regulation has been harmonized and restructuring processes have taken place under the supervision of the European Central Bank. Its objective has been to obtain a banking model for the whole of Europe, so that in times of financial crisis (such as 2007–2009), it is capable of overcoming its financial difficulties, for which it is necessary to limit certain banking operations or activities (Alexander, 2015).

Therefore, the aim of our paper is to analyze the efficiency in the banking sector. We analyze data in consolidated financial statements in a sample of 471 banks during the period 2005–2022 from 39 countries. This is an extended period covering different business cycles, including the most recent COVID-19 crisis. To reflect this in the model, macroeconomic control variables have been included. The empirical study is divided into two stages. In the first stage, the efficiency scores of each bank are calculated using the DEA methodology (BCC model), both input-oriented and output-oriented. In a second stage, a Tobit regression model is run to determine which variables significantly affect banks' efficiency scores.

The results show that the efficiency scores are similar in the input-oriented and output-oriented model, and the banks that are efficient (efficiency score = 1) considering the input approach are also efficient when focusing on maximizing the outputs. The application of the Tobit model shows that the variables that positively affect efficiency are the ROA, the size of the bank, the capital ratio and liquidity. Those coefficients are very similar in magnitude for both input and output focus. On the other hand, from the negative side of the effects, the variables

that decrease the extent of efficiency are the provisions ratio and the fact of being a financial entity under the Single Supervisory Mechanism (SSM), also is similar in the input and output orientation.

2. Literature background

2.1 Overview of the European banking industry

The banking sector is one of the main drivers of any developed economy (Tarasenko *et al.*, 2022). For this reason, different aspects related to this sector have been the subject of research in numerous studies (Bayar *et al.*, 2021).

In recent decades, the European banking sector has undergone significant transformation, including restructuring, concentration and changes in regulation and supervision. In addition, due to their systemic risk, the decisions of individual banks can have global consequences in the markets (Miloș and Miloș, 2022). This has aroused the interest of academics and policymakers alike (Fang *et al.*, 2011). Numerous research studies have carried out comparative studies of banking systems in different countries (Christopoulos *et al.*, 2020; Shala and Toçi, 2021). However, despite the heterogeneity of this sector in Europe, commonalities can be identified in its transformation and development process that allow for learning from best practices and decisions on regulation and activity in the banking sector (Butzbach *et al.*, 2020). In the case of the EU, the Memorandum of Understanding (MoU) was signed, which includes measures mainly concerning restructuring, recapitalization and loss-sharing measures.

Following phases or periods of economic crisis, a number of reforms have been implemented with the aim of aligning regulatory and supervisory standards in the European financial sector. From a supervisory point of view, in 2012 EU members agreed to start the process toward banking union through three pillars (Arrigoni and Rivolti, 2022): the SSM, with the European Central Bank as the centralized supervisor; the Single Resolution Mechanism, to coordinate bank resolution; and a common European Deposit Guarantee Scheme (Duro and Ormazabal, 2018). Several studies show how transformation of the banking system by restructuring and recapitalization have lead to improvements in solvency, profitability and efficiency of the banking sector (Cruz-García *et al.*, 2018; Gropp and Vesala, 2004)

2.2 Efficiency analysis and its relevance to the banking sector

2.2.1 Impact of regulation and macroeconomic factors on bank efficiency. The supervisory function of banking regulators affects risk-taking policy, reducing the risk (Barth *et al.*, 2004; Demirgüç-Kunt *et al.*, 2008; Shehzad and De Haan, 2015). However, there is no a common agreement in literature, as shown by other authors evidencing the fact that more control by supervisors is not associated with less banking risk (Beltratti and Stulz, 2012; Demirgüç-Kunt and Detragiache, 2011; González, 2005). Bank efficiency decreases as Central Bank supervision increases, for banks are less profit-efficient when located in countries with more unified banking supervisory authorities (Chortareas *et al.*, 2013; Gaganis and Pasiouras, 2013). At the same time, fines and sanctions imposed by banking supervisors are counterproductive due to a decrease in moral hazard in banking (Kupiec and O'Brien, 1995; Prescott, 1999).

On the other hand, banking reforms to adapt to the Basel guidelines have not always led to an improvement in the efficiency of banking institutions, but that it depends on the characteristics of each country (Barth *et al.*, 2008). Notwithstanding this, banking supervision is positive for efficiency because it limits risk taking, making banks more prudent and, hence, improving their efficiency (He *et al.*, 2021; Mirzaei and Samet, 2022).

Gross domestic product (GDP) has been considered a significant variable in several empirical studies as a variable affecting bank efficiency (Blanco-Oliver, 2021; Chortareas *et al.*, 2012; Drake *et al.*, 2006; He *et al.*, 2021; Lozano-Vivas and Pasiouras, 2010).

However, according to the literature, there is no unanimous position on its influence, with authors stating a positive relation on efficiency (Gaganis and Pasiouras, 2013; Maudos *et al.*, 2002; Vu and Nahm, 2013), versus others positing a negative relationship (Avkiran, 2009; Řepková, 2015).

2.2.2 Relationship between bank performance and efficiency. Numerous authors have analyzed the relationship between bank performance and efficiency from different perspectives (Feng and Zhang, 2012; Pessarossi and Weill, 2015; Tan and Floros, 2013). To that end, profitability, liquidity and solvency are essential value drivers (Bazih and Vanwalleghem, 2021; Chang *et al.*, 2018; Choi *et al.*, 2016; Miloș and Miloș, 2022).

In different context, prior literature has analyzed several variables of bank entities that affect efficiency, such as bank size (Antunes *et al.*, 2022; Sarmiento and Galán, 2017; Thi My Phan *et al.*, 2016; Vu and Nahm, 2013), profitability (Antunes *et al.*, 2022; Delis *et al.*, 2017; Vu and Nahm, 2013) or capitalization (Řepková, 2015; Sarmiento and Galán, 2017). Others consider the effect of several types of risks (liquidity, portfolio, credit, market or operational risks, among others) on efficiency (Bhatia *et al.*, 2018; Řepková, 2015; Sarmiento and Galán, 2017; Sun and Chang, 2011; Thi My Phan *et al.*, 2016) and the impact of risk diversification (Rossi *et al.*, 2009). The effect of nonperforming loans (NPLs) is also considered, conditioned by the degree of capitalization and whether or not they belong to a banking group (Phung *et al.*, 2022; Ramli *et al.*, 2018). Finally, also macroeconomic variables such as interest rates or GDP (Řepková, 2015) are considered.

Hence, there is no consensus on which factors of banks affect their efficiency (Degl'Innocenti *et al.*, 2017; Řepková, 2015). The main contribution of this study is a more comprehensive and global approach that includes aspects of the most important insights from the previous literature, over a very extended period and also including bank and macroeconomic environment characteristics.

2.3 Hypotheses development

Based on the previous literature review, the following hypotheses have been put forward in this study to be contrasted and tested.

Size is a variable that conditions many aspects of business performance and the way in which this performance impacts on bank efficiency (Antunes *et al.*, 2022; Bazih and Vanwalleghem, 2021; Choi *et al.*, 2016; Sarmiento and Galán, 2017; Vu and Nahm, 2013). In addition, seniority as a variable has been used in recent research on firms in different sectors of activity (Flores-Ureba *et al.*, 2023; Gelashvili *et al.*, 2023; Pacheco, 2023). In the light of the above:

H1. Bank characteristics, age and size, determine its efficiency.

GDP is a magnitude that has been considered by many authors as a control variable in models that try to explain the variables that affect bank efficiency (Blanco-Oliver, 2021; Chortareas *et al.*, 2012; Drake *et al.*, 2006; He *et al.*, 2021). In any case, their relationship has in some cases been positive (Cruz-García and Maudos, 2016; Gaganis and Pasiouras, 2013; Vu and Nahm, 2013), while negative in others (Avkiran, 2009; Řepková, 2015). Therefore:

H2. The economic environment influences efficiency.

About other economic and financial characteristics of the banks, some variables of interest are liquidity (intermediation ratio between loans and deposits) (Chang *et al.*, 2018; Dietsch and Lozano-Vivas, 2000), profitability (Antunes *et al.*, 2022; Řepková, 2015; Vu and Nahm, 2013) and financial solvency (Choi *et al.*, 2016; Řepková, 2015). Considering this:

H3. The economic-financial situation of the bank influences its efficiency.

Bank credit risk is related to efficiency (Bhatia *et al.*, 2018; Delis *et al.*, 2017; Sarmiento and Galán, 2017; Sun and Chang, 2011). Some efficiency studies have focused on credit risk measured in terms of NPLs, provisions and loan portfolio (Phung *et al.*, 2022; Ramli *et al.*, 2018). Others, outside the efficiency framework, consider off-balance sheet risk to be relevant as part of the bank's indirect but significant credit risk (Haq *et al.*, 2022; Karn *et al.*, 2022; Xie *et al.*, 2023). Therefore:

H4. The bank's credit risk influences efficiency.

Bank regulation mechanisms affect bank efficiency (Barth *et al.*, 2004, 2008; Demirgüç-Kunt *et al.*, 2008; Shehzad and De Haan, 2015). The greater the control exercised by these bodies, the more they reduce banking risk and thus enhance efficiency (Beltratti and Stulz, 2012; Chortareas *et al.*, 2013; Gaganis and Pasiouras, 2013; González, 2005). Hence:

H5. The single European banking supervision mechanism conditions the level of efficiency.

3. Data and methodology

3.1 Method: data envelopment analysis

Efficiency measurement has evolved over time. In general terms, efficiency has been measured since the earlier studies by Farrell (1957) by comparing the input necessary to obtain a certain output. However, such primary measures considered a single input and output and, hence, a partial productivity (Cooper *et al.*, 2006), limiting the application of these studies (Bhatia *et al.*, 2018; Lita and Stamule, 2018). The complexity of the economic relationships make it necessary new techniques that are able to account for the combination of several inputs and outputs in a single ratio, because more than one outputs may be attributable to the same or several inputs (Bhatia *et al.*, 2018; Bowlin, 1998; Cooper *et al.*, 2006; Deville, 2009).

The DEA is a methodology based on mathematical programming to obtain optimal relationships between a group of inputs and a group of outputs (Bhatia *et al.*, 2018; Ji and Lee, 2010; Lita and Stamule, 2018) to assess the performance of a set of homogeneous entities known as decision-making units (DMUs; Lita and Stamule, 2018; Noman and Fernández Uclés, 2024), assigning optimally the weights for each variable without the need of previously define those weights (Cooper *et al.*, 2006). It is necessary that every DMU has the control in the transformation of inputs into outputs (Lita and Stamule, 2018). Besides, as opposed to other efficiency parametric methodologies, DEA, as a nonparametric one, does not need to specify the random error (Bhatia *et al.*, 2018). DEA has become the most prevalent methodology for efficiency analysis in literature (Noman and Fernández Uclés, 2024).

The objective of DEA differs from the regression because it searches for the observations that best perform (efficient observations) and make a comparison of how the rest of observations deviate from the optimal performance, represented by an efficient frontier that envelops them, while regression considers the average (central) tendency behavior of a group of observations, which is not optimal (Cooper *et al.*, 2006). The optimization process can be oriented in two different ways: maximize outputs given a certain level of inputs (output-oriented DEA) or minimize the necessary inputs to obtain a certain level of outputs (input-oriented DEA) (Charnes *et al.*, 2013).

The first DEA application was proposed by Charnes *et al.* (1978) (CCR model). This model is based on constant returns to scale, which is valid only if all DMUs operate on the same optimal scale, but DMUs operating with different conditions may cause problems, confounding technical efficiency with a mere scale effect (Chen and Soo, 2010; Lita and Stamule, 2018; Wang *et al.*, 2014). To overcome this, the variable-returns-to-scale model by Banker, Charnes and Cooper (1984) (BCC model) enables calculating technical efficiency with DEA without scale effect (Chen and Soo, 2010). We consider BCC model given the great differences in the operating environment of the banks in our sample due to different sizes, countries and legal environments. We analyze both the input-oriented and the output-oriented approach because in bank efficiency literature there is evidence that multiple factors improve efficiency both for a reduction of expenses (inputs) (to cite some examples: Bitar *et al.*, 2016; Naceur and Omran, 2011; Pessarossi and Weill, 2015; Sarmiento and Galán, 2017), and for an increase in profitability indicators (outputs) (Bitar *et al.*, 2016).

The mathematical modeling of the optimization process following the BCC model is defined in Table 1, where X represents the vector of inputs, Y represents the vector of outputs, $s+$ and $s-$ are the slacks, λ are the coefficients to be optimized and $\varnothing$ are the efficiency scores.

The results of the DEA analysis yield an efficiency score, $\varnothing$, for every DMU, ranging 0–1 values (Drake *et al.*, 2006). Entities with efficiency score of 1 are considered efficient, and their graphical representation forms the efficiency frontier (Ji and Lee, 2010; Noman and Fernández Uclés, 2024; Samoilenko, 2014). On the contrary, DMUs below 1 (100%) are considered inefficient as compared with the rest of entities and can improve their performance by either reducing inputs or increasing outputs (Drake *et al.*, 2006; Lita and Stamule, 2018).

The efficiency scores can be used as a variable of efficiency to analyze its determinants or consequences. In our study, we obtain the efficiency scores to further analyze the determinants of a greater or lower efficiency according to several factors (macroeconomic or firm-characteristic factors).

3.2 Research design: model and variables

To analyze the determinants of bank efficiency in a wide economic period (2005–2022), the proposed steps are the following. In the first phase, efficiency scores are calculated for every bank entity (DMU). In the second phase, a Tobit regression model is run to observe which of a set of potential efficiency determinants significatively affect the efficiency score of banks. Next, we describe the variables to be considered in each phase and the estimation process.

Table 1. BCC models

Input-oriented (BCC_I)	Output-oriented (BCC_O)
$min_{\varnothing,\lambda,s^+,s^-}$ $z_0 = \varnothing - \varepsilon \cdot \overrightarrow{1} s^+ - \varepsilon \cdot \overrightarrow{1} s^-$	$max_{\varnothing,\lambda,s^+,s^-}$ $z_0 = \varnothing + \varepsilon \cdot \overrightarrow{1} s^+ + \varepsilon \cdot \overrightarrow{1} s^-$
Subject to: $\varnothing X_0 - X\lambda - s^- = 0$	Subject to: $\varnothing Y_0 - Y\lambda + s^+ = 0$
$\underrightarrow{Y\lambda} - s^+ = Y_0$	$\underrightarrow{X\lambda} + s^- = X_0$
$\overrightarrow{1}\lambda = 1$	$\overrightarrow{1}\lambda = 1$
$\lambda, s^+, s^- \geq 0$	$\lambda, s^+, s^- \geq 0$

Source(s): Authors' own creation based on Charnes *et al.* (2013)

3.2.1 Phase 1: Obtention of efficiency scores with data envelopment analysis. The first step is the definition of the inputs and outputs to compare the efficiency among the DMUs. There is no common agreement in banking literature regarding the inputs and outputs to be considered (Blanco-Oliver, 2021; Deville, 2009). Notwithstanding this, Bowlin (1998) suggests that input and output selection are based on usual relationships between both that can be reasonably expected, are representative for performance evaluation and control of firms, and that managers are involved in them with their decisions. In particular, this study considers a model with two inputs (operating expenses and general expenses) and two outputs (operating revenues and earnings before taxes). The description of the input and output variables is detailed in Table 2.

Before running the DEA models (both BCC_I and BCC_O), the data are to be depurated in a double sense. First, the DEA is not suitable for negative values of the variables, which could alter the optimization process of comparison among the DMUs (Bhatia *et al.*, 2018; Bowlin, 1998), as well as the presence of outliers, because the DEA uses precisely extreme values to determine DMUs that are fully efficient (Noman and Fernández Uclés, 2024). We drop negatives and apply a super-efficiency model to detect the outliers and eliminate these observations as well. For the super-efficiency analysis, we use the EMS Software (freely available) and consider as the threshold for elimination those observations with efficiency scores above or equal to a value of 2.0 (Martinez-Nunez and Pérez-Aguiar, 2014; Noman and Fernández Uclés, 2024).

Once observations are depurated from negative values and outliers (further details are presented in the epigraph 3.3 about the sample selection process), we proceed to run the DEA model to obtain the efficiency scores, using the MAX-DEA Software (freely available).

3.2.2 Phase 2: Regression analysis. The objective in this phase is to test the hypotheses that efficiency is related with both macroeconomic (*H2*), regulatory (*H5*) and firm-specific (*H1*, *H3* and *H4*) variables.

We use Tobit regression, which is prevalent in literature to find the determinants of efficiency gaps among the DMUs (Blanco-Oliver, 2021; Drake *et al.*, 2006; Ji and Lee, 2010; Thi My Phan *et al.*, 2016). The dependent variable in the model is the efficiency score of the bank entities and the independent variables are the potential facts explaining their efficiency. The variable is censored at value = 1 because, precisely, only banks with efficiency scores = 1 are considered efficient.

About the independent variables, macroeconomic conditions are related with efficiency because banks operating in environments with greater economic development have more opportunities to obtain more outputs with rapid growth (Blanco-Oliver, 2021; Dietsch and Lozano-Vivas, 2000; Thi My Phan *et al.*, 2016) because of the obtention of more competitive interest rates and profit margins (Dietsch and Lozano-Vivas, 2000). Consequently, the GDP of the country can determine the possibilities of efficiency of the banks that operate in such environment. Notwithstanding this, there is controversy in literature because other authors

Table 2. Input and output DEA variables

Variables		Definition
Operating expenses	Input	Sum of expenses from interests and commissions
General expenses	Input	Sum of general, personnel, depreciation and operating expenses
Operating revenues	Output	Sum of revenues from interests and commissions
Earnings before taxes	Output	Earnings before income taxes

Source(s): Authors' own creation

have provided evidence of a negative relationship between GDP and efficiency (for example: Avkiran, 2009; Řepková, 2015). Given the controversy in prior literature, we cannot predict the sign for the relationship between GDP and efficiency. In addition, the economic stability also favors the potential for more efficient entities, being inflation an indicator of the stability of the country (Blanco-Oliver, 2021; Thi My Phan *et al.*, 2016). The relationship between inflation and efficiency is expected to be negative because greater inflation is indicative of lower economic stability. Macroeconomic variables are connected with *H2*.

In addition, different geographical locations also affect the regulatory system, which can impose different conditions regarding banking structure or accessibility to certain services, being regulation a differential aspect between financial entities (Bhatia *et al.*, 2018; Dietsch and Lozano-Vivas, 2000). We, hence, include in the model a dummy variable to account for the regulatory effect, which is the fact of banks being under the Single Supervisory Mechanism (dummy variable D_SSM). Regarding the expected sign, there is controversy in literature, because part of the authors understand that supervising banking authorities help to control management of banks, reducing their extent of risk and, thus, improving efficiency (Barth *et al.*, 2004; Demirgüç-Kunt *et al.*, 2008; Shehzad and De Haan, 2015), whereas others show that greater control is not linked to lower risk and can even provoke negative externalities, such as a lower competitiveness (Blanco-Oliver, 2021; Chortareas *et al.*, 2012, 2013; Degl'Innocenti *et al.*, 2017). Because of that, we cannot predict the sign of the variable D_SSM in the model. The regulatory variable D_SSM enables testing for the *H5*.

Regarding individual characteristics of the financial entities, being more mature or having a greater size can affect the level of efficiency of financial entities (see, as some examples: Peng *et al.*, 2017; Ramli *et al.*, 2018; Řepková, 2015; Thi My Phan *et al.*, 2016). For that reason, we include in the model both the age of the bank and its size in terms of assets (albeit modulated with the natural logarithm instead than with gross level of assets). For both variables, we expect a positive sign. These two variables will analyze *H1*.

In addition, also at the individual level, various value drivers are essential for evaluating the performance of financial entities: profitability, liquidity and solvency (Bazih and Vanwalleghem, 2021; Chang *et al.*, 2018; Choi *et al.*, 2016). Liquidity and solvency are closely linked to risk management in banks (Bhatia *et al.*, 2018), because the effort for risk reduction leads to better allocation of resources and, even, greater achievement of outputs (Blanco-Oliver, 2021; Řepková, 2015; Thi My Phan *et al.*, 2016). Similarly, greater profitability implies obtaining better outputs. In this study, solvency is analyzed using the capital ratio, liquidity is included via the liquidity ratio, and for profitability the variable in the model is the ROA. Regarding the expected signs, a positive relationship is expected for both. These three variables are used to test for *H3*.

Finally, we include the provision ratio, as banks' effort to deal with negative situation of NPLs implies increasing their inputs, thus diminishing efficiency (Phung *et al.*, 2022; Ramli *et al.*, 2018; Thi My Phan *et al.*, 2016). We also consider off-balance sheet risk as determinant of actual risk (Haq *et al.*, 2022; Karn *et al.*, 2022; Xie *et al.*, 2023). We expect a negative association with efficiency, being these variables connected with *H5*.

The proposed model is the following:

$$Eff\_Score^{*} = \beta_0 + \beta_1 Age + \beta_2 Size + \beta_3 GDP + \beta_4 Inflation + \beta_5 Capital\_ratio + \beta_6 Liquidity\_ratio + \beta_7 ROA + \beta_8 Provision\_ratio + \beta_9 Off\_balance + \beta_{10} D\_SSM + \varepsilon$$

The description of the variables is detailed in Table 3.

Table 3. Tobit regression variables

Variable		Definition	Source
Eff_Score	Dependent	Efficiency scores obtained from DEA model, both output-oriented and input-oriented	Banker, Charnes and Cooper (1984)
Age	Independent	Difference between 31.12 of the year of the data and the year of establishment of the company	Orbis data base
Size	Independent	Natural logarithm of total assets	
Capital_ratio	Independent	Book equity to risk weighted assets	
Liquidity_ratio	Independent	Total loans scaled by total deposits	
ROA	Independent	Net income scaled by total assets	
Provisions_ratio	Independent	Loan loss reserves scaled by gross loans	
Off_balance	Independent	Off-balance-sheet exposures, where a bank has underwritten the obligations of a third party and currently stands behind the risk	
D_SSM	Independent	Dummy variable taking the value of 1 if the bank entity is under the Single Supervisory Mechanism, and 0 otherwise	European Central Bank
GDP	Independent	Annual rate of change in gross domestic product of the country where the bank entity is located	World Bank
Inflation	Independent	Annual rate of change in Consumer Price Index of the country where the bank entity is located	

Source(s): Authors' own creation

3.3 Sample selection

To analyze the efficiency in the banking sector, we analyze data in consolidated financial statements in a sample of 471 banks during the period 2005–2022 from 39 countries. This is an extended period covering different business cycles, including the most recent COVID-19 crisis. To reflect this in the model, macroeconomic control variables have been included.

Data are obtained from the Orbis database. We require full observations for the two inputs and the two outputs, eliminate negative values, and next, perform the super-efficiency DEA to eliminate the outliers. The detailed number of observations can be seen in Table 4.

In next section, we present the results for the two phases previously described.

4. Results and discussion

4.1 Results for the efficiency scores with data envelopment analysis

After the depuration process for the sample, and prior to the application of DEA, let us present in Table 5 the descriptive statistics of the input and output variables for efficiency calculation.

Table 4. Sample selection

	N° obs
Obs. Full information input/output variables	6,729
- Obs. With negative values input/output variables	827
- Outliers	113
Final N° obs. For DEA estimation	*5,789*

Source(s): Authors' own creation

Table 5. Descriptive statistics for DEA variables (millions EUR)

Variable	Type	Mean	Median	St. dev.	Min	Max	Skewness
Operating expenses	Input	1,323.83	0.21	4,071.45	0.179	56,900.00	5.91
General expenses	Input	1,247.03	0.22	3,456.40	0.001	32,500.00	4.97
Operating revenues	Output	2,880.19	0.54	7,855.75	0.003	75,100.00	4.95
Earnings before taxes	Output	0.52	0.10	1,403.34	0.025	17,500.00	5.46

Source(s): Authors' own creation

The main highlight in Table 5 is the great dispersion of the data for both the input and output variables. This fact is due to the heterogeneity of the bank characteristics, mainly due to their size. In addition, the fact that the bank entities are located in up to 39 different countries exacerbate that difference due to different macroeconomic conditions, being one of the most important ones is the own country GDP.

After the application of BCC DEA, both input-oriented and output-oriented, we obtain the efficiency scores for each firm-year observation. The analysis has been carried out performing the DEA model by year, because the DEA compares groups of entities, then the same entity cannot have observations in different years. In Table 6, we describe by year the average efficiency scores for the banks, both in the input- and output-oriented BCC model, as well as the number of efficient banks.

As observed in Table 6, the efficiency scores are similar in the input-oriented and output-oriented model (slightly higher for maximization of outputs), and the banks that are efficient (efficiency score = 1) considering the input approach are also efficient when focusing on maximizing the outputs. This may enable obtaining robust conclusions when analyzing the factors affecting the efficiency.

Table 6. Average efficiency scores and number of efficient banks by year

	Average efficiency score		Efficient banks	
Year	*Output-oriented*	*Input-oriented*	*Frequency*	*%*
2005	0.8051	0.8033	28	6.68
2006	0.7899	0.7876	25	5.94
2007	0.7563	0.7490	30	7.85
2008	0.7859	0.7830	24	5.77
2009	0.6896	0.6862	14	3.53
2010	0.7771	0.7733	27	6.82
2011	0.7424	0.7386	16	4.32
2012	0.7591	0.7540	19	5.65
2013	0.7748	0.7740	22	6.88
2014	0.7571	0.7514	30	9.58
2015	0.7556	0.7501	23	8.75
2016	0.7111	0.7076	22	8.30
2017	0.6845	0.6814	21	7.98
2018	0.6871	0.6819	15	6.00
2019	0.6796	0.6768	21	9.33
2020	0.6958	0.6937	16	5.88
2021	0.6952	0.6931	20	7.38
2022	0.6596	0.6517	25	11.90

Source(s): Authors' own creation

Considering the percentage of efficient banks, we observe the noteworthy increase in the last year of the study, 2022, with nearly 12% of the banks being efficient. This denotes a great effort by the financial entities to make the best of their resources to get better results. The percentage is strongly linked to the economic cycles, as observed with the lowest percentage of efficient banks during the two financial crises in our period of study: the sub-prime crisis (2008–2013), and the COVID-19 crisis (2020, maintaining the negative consequences even in 2021). This fact is in line with prior studies associating a loss of efficiency during financial crises because of a decrease in the extent of lending activity during those periods, decreasing the performance of the entities, especially from the output side (Degl'Innocenti *et al.*, 2017).

It is remarkable as well that despite the high percentage of efficient banks in 2022, the average efficiency score is, surprisingly, the lowest in the analyzed period (0.6596 for the output orientation and 0.6517 in the input). This fact evidences greater heterogeneity in the performance, with worse performance of the nonefficient firms as compared with other periods.

4.2 Results for the factors affecting efficiency

Before presenting the estimation results, let us present the descriptive statistics of the variables that conform the Tobit regression analysis in Table 7.

The data observed in Panel A reflect heterogeneity in macroeconomic variables and bank characteristics, which generates deviations in solvency, liquidity, profitability and risk. Notwithstanding that, in general, the median values (p50) are close to the mean values. As observed in Panel B of Table 7, the correlation between the independent variables is not high and, hence, there are no collinearity problems.

We present the results of the Tobit regression in Table 8 (output-oriented efficiency) and Table 9 (input-oriented efficiency).

As observed in Tables 8 and 9, the variable that most affects efficiency, both if we consider maximizing outputs or minimizing inputs is the profitability, as reflected by ROA having a coefficient of 0.0726, statistically significant even at 1%. Then, more profitable banks evidence an increase of their efficiency, as reflected in other studies (Blanco-Oliver, 2021).

The second factor that positively affects efficiency is the size of the bank entity. Larger companies obtain a greater number of outputs given their current extent of inputs and evidence a greater ability to minimize the necessary number of inputs to reach the current level of outputs. Other studies in prior literature have also evidenced this positive effect of size on bank efficiency (Bhatia *et al.*, 2018; Blanco-Oliver, 2021; Degl'Innocenti *et al.*, 2017; Peng *et al.*, 2017; Ramli *et al.*, 2018; Thi My Phan *et al.*, 2016).

For that reasons, governments should be careful when imposing limits to the size of banks, because insufficient bank size may lead to a decrease in productivity (Degl'Innocenti *et al.*, 2017). Moreover, there is evidence that despite higher coordination costs for larger banks, these entities have greater efficiency because of several facts such as better opportunities for diversification (lowering, thus, credit and idiosyncratic risks), more economies of scale (lower unit fixed costs because total costs are distributed between more transactions) or better conditions when accessing financial markets (greater margins) (Blanco-Oliver, 2021). Furthermore, greater banks, generally more competitive, have greater likelihood to survive in the long term, and this encourages them to invest in knowledge and innovation, making them more attractive for customers (Bhatia *et al.*, 2018; Blanco-Oliver, 2021).

On the other hand, the capital ratio and liquidity ratio also positively affect bank efficiency. This positive effect of both capital and liquidity is in line with the fact that when

Table 7. Descriptive statistics for Tobit regression variables

Variable	N	Mean	St dev	p25	p50	p75	Min	Max
Panel A: Descriptive statistics								
Eff_Score_input	5,789	0.72	0.14	0.62	0.70	0.81	0.30	1.00
Eff_Score_output	5,789	0.73	0.14	0.63	0.71	0.81	0.30	1.00
Age *(days)*	4,482	27,445.09	14,543.30	11,297.00	36,842.00	40,540.00	518.00	44,924.00
Size	5,788	16.41	1.92	15.16	16.30	17.41	11.05	21.70
GDP (%)	5,775	1.88	3.71	0.83	1.98	3.24	−29.10	24.48
Inflation (%)	5,746	2.74	4.59	0.77	1.75	2.81	−2.10	72.31
Capital_ratio (%)	4,808	18.49	8.11	14.20	17.24	20.70	1.75	172.00
Liquidity_ratio	5,693	0.99	1.79	0.70	0.90	1.04	0.00	78.29
ROA (%)	5,789	0.83	0.84	0.37	0.63	1.06	−3.02	20.26
Provision_ratio (%)	5,555	3.22	4.57	1.03	2.20	3.71	0.00	93.05
Off_balance *(millions EUR)*	5,638	19,500.00	61,400.00	362.95	1,611.58	5,625.77	−1,174.95	889,000.00
D_SSM	5,789	0.36	0.48					

Panel B: Correlation matrix

	Eff_Score_input	Eff_Score_output	Age	Size	GDP	Inflation	Capital_ratio	Liquidity_ratio	ROA	Provision_ratio	Off_ balance
Eff_Score_output	0.982*	1									
Age	−0.095*	−0.095*	1								
Size	0.166*	0.244*	0.030*	1							
GDP	0.039*	0.042*	−0.057*	0.002	1						
Inflation	0.070*	0.071*	−0.106*	−0.025	0.204*	1					
Capital_ ratio	−0.026	−0.050*	0.042*	−0.222*	0.013	0.009	1				
Liquidity_ ratio	0.039*	0.037*	0.030*	0.042*	−0.008	−0.004	0.004	1			
ROA	0.280*	0.271*	−0.315*	−0.242*	0.138*	0.170*	0.085*	−0.034*	1		
Provision_ ratio	−0.030*	−0.033*	−0.145*	−0.157*	−0.041*	0.061*	−0.043*	0.029*	0.194*	1	
Off_ balance	0.185*	0.225*	0.022*	0.559*	−0.008	−0.030*	−0.087*	−0.029*	−0.141*	−0.062*	1
D_SSM	−0.297*	−0.292*	0.106*	0.049*	−0.014	−0.160*	0.224*	−0.009	−0.152*	−0.029*	0.008

Note(s): *Means statistical significance at 0.05
Source(s): Authors' own creation

Table 8. Results from Tobin regression for output-oriented efficiency

	Coef.	St. dev.	*t*-stat	*p*-value	Hypothesis verification
Age	0.0000***	0.0000	−3.8300	< 0.001	*H1* (No)
Size	0.0223***	0.0014	16.1100	< 0.001	*H1* (Yes)
GDP	−0.0012**	0.0006	−2.0000	0.0450	*H2* (Yes)
Inflation	−0.0007	0.0005	−1.5600	0.1180	*H2* (No)
Capital_ratio	0.0010***	0.0003	3.4900	< 0.001	*H3* (Yes)
Liquidity_ratio	0.0022**	0.0009	2.3600	0.0180	*H3* (Yes)
ROA	0.0726***	0.0031	23.3400	< 0.001	*H3* (Yes)
Provision_ratio	−0.0017***	0.0004	−3.8500	< 0.001	*H4* (Yes)
Off_balance	0.0000***	0.0000	6.7100	< 0.001	*H4* (No)
D_SSM	−0.0685***	0.0046	−14.7800	< 0.001	*H5* (Yes)
_cons	0.3297***	0.0254	12.9900	< 0.001	

Note(s): ***, **and * mean statistical significance at 0.01, 0.05 and 0.1 levels, respectively
Source(s): Authors' own creation

Table 9. Results from Tobin regression for input-oriented efficiency

	Coef.	Std.	*t*-stat	*p*-value	Hypothesis verification
Age	0.0000***	0.0000	−3.8000	< 0.001	*H1* (No)
Size	0.0171***	0.0014	12.0900	< 0.001	*H1* (Yes)
GDP	−0.0012**	0.0006	−2.0000	0.0450	*H2* (Yes)
Inflation	−0.0009*	0.0005	−1.7800	0.0760	*H2* (No)
Capital_ratio	0.0010***	0.0003	3.5000	< 0.001	*H3* (Yes)
Liquidity_ratio	0.0026***	0.0010	2.6800	0.0070	*H3* (Yes)
ROA	0.0721***	0.0032	22.5900	< 0.001	*H3* (Yes)
Provision_ratio	−0.0019***	0.0004	−4.1900	< 0.001	*H4* (Yes)
Off_balance	0.0000***	0.0000	6.2600	< 0.001	*H4* (No)
D_SSM	−0.0703***	0.0048	−14.7700	< 0.001	*H5* (Yes)
_cons	0.4115***	0.0260	15.8000	< 0.001	

Note(s): ***, **and * mean statistical significance at 0.01, 0.05 and 0.1 levels, respectively
Source(s): Authors' own creation

banks have tried to focus excessively their attention on reinforcing their capital and liquidity position, such as during financial crisis periods, they finally decrease their volume of lending activities, diminishing that way the obtained outputs (Degl'Innocenti *et al.*, 2017). The liquidity risk has a negative effect on efficiency, then firms increasing their efforts to improve liquidity eventually achieve greater efficiency levels, both technical (output orientation) and allocative (input orientation) (Blanco-Oliver, 2021; Řepková, 2015; Thi My Phan *et al.*, 2016). Also, lower capital ratios lead to lower efficiency because having less amount of equity implies assuming higher risks at a greater leverage, thereby increasing the amount of borrowing costs (Dietsch and Lozano-Vivas, 2000).

From the negative side of the effects, efficiency decreases with the provisions ratio and the fact of being a financial entity under the SSM. Regarding the latter, this negative sign is in accordance with prior literature. Despite the efforts for greater intervention of the governments to improve the allocation of financial resources and promote more competition

among banks, in reality, regulatory impositions on the banking sector have brought about negative externalities, such as a lower competitiveness (Blanco-Oliver, 2021; Chortareas *et al.*, 2012, 2013; Degl'Innocenti *et al.*, 2017). Besides, when banks are under a stricter supervision, they tend to relax their efforts to be accountable to their shareholders and, thus, to look for more efficient decisions to show for others (Chortareas *et al.*, 2013) or for new and attractive activities for their clients (Bhatia *et al.*, 2018). In the end, economies with higher freedom can achieve better economic outcomes.

The negative effect for the provision ratio is consistent with prior evidence in literature that the fact of having a greater extent of NPLs leads banks to expand their resources to monitor the borrowers (Phung *et al.*, 2022; Ramli *et al.*, 2018; Thi My Phan *et al.*, 2016). The negative effect is, however, mitigated when banks have better levels of capitalization (Phung *et al.*, 2022).

4.3 Additional analyses

Because the period of study includes different economic cycles, we have tested using the Kolmogorov−Smirnov test for potential time-series variation in the periods of pre-crisis and post-crisis in the two crisis periods: the financial sub-prime crisis (using as the benchmark year 2009), and the COVID-19 crisis (using as the benchmark year 2020). The results are not conclusive of a difference in the pre-crisis and post-crisis periods when considering specifically the two aforementioned crisis periods. Time variance in the efficiency score is observed, instead, for the full sample, irrespective of the economic cycle, thereby suggesting that it is not the crisis what determines efficiency score variance throughout the time period of study.

In addition, we have checked that the model has homoskedasticity by performing the Breusch−Pagan test for constant variance (p-value = 0.4920, then the constant variance hypothesis cannot be rejected).

Finally, we have checked for potential endogeneity by regressing the residuals of the Tobit regressions (both input- and output-oriented) with all explanatory variables, obtaining p-values for the coefficients above 0.1, thereby indicating absence of endogeneity, for the residuals are not correlated with any of the explanatory variables.

5. Conclusion and implications

This study examined the efficiency of the European banking sector using DEA methodology and Tobit regression to identify key determinants. The findings reveal that both input- and output-oriented models yield similar efficiency scores, underscoring the robustness of the DEA approach. Key factors enhancing efficiency include profitability, size, capital ratio and liquidity. Conversely, provisions for NPLs and being under the SSM negatively impact efficiency. The results suggest that larger and more profitable banks, with adequate capital and liquidity, use resources more effectively. However, regulatory constraints and higher provisions for NPLs can hinder efficiency. These findings have important implications.

To boost bank profitability, policymakers should implement tax incentives and support innovation in the banking sector. This includes offering R&D tax credits, grants for technological advancements and subsidies for adopting new banking technologies. In addition, a regulatory environment that promotes profit-generating activities while maintaining stability is crucial. Simplifying compliance procedures and reducing regulatory burdens can allow banks to focus more on enhancing profitability. At the meantime, encouraging mergers and acquisitions, as well as supporting national and international expansion through financial incentives and the reduction of barriers, can generate economies of scale, improving efficiency and contributing to the growth of the sector.

The stability of the banking sector depends on maintaining strict capital and liquidity requirements. Regulators must ensure that banks are sufficiently capitalized through regular stress tests and minimum liquidity ratio requirements. These policies ensure that banks can withstand economic shocks without compromising their operational stability. Specifically, stress tests, implemented by bodies such as the European Banking Authority (EBA), are essential tools for assessing the capacity of banks in the face of adverse macroeconomic scenarios. Studies such as Schmaltz *et al.* (2014) indicate that efficiency in capital and liquidity management is key to passing these tests. In addition, recent research has explored how operational efficiency is correlated with greater resilience to economic shocks. Casu *et al.* (2020) highlight that technical efficiency improves adaptability under stress. Likewise, Dissem and Lobez (2020) analyze the correlation between 2014 stress tests and market-based measures of systemic risk, highlighting how efficiency could be a relevant factor in resilience assessment.

The results of our study show that variables such as capital ratio and liquidity have a positive impact on efficiency, suggesting that more efficient banks may also be better prepared to pass these tests. However, establishing a direct causal connection between efficiency and resilience requires further analysis. An interesting focus for future research would be to examine whether banks identified as more efficient according to our model are more likely to pass EU stress tests or withstand adverse economic conditions.

Likewise, the impact of SSM on bank efficiency is a topic of growing interest. Altunbaş *et al.* (2022) note that the SSM has improved transparency in risk disclosure, although it has also increased pressure on banks to comply with stricter standards. In addition, Abad *et al.* (2023) compare how stress testing programs affect the perception of credit risk in Europe and the USA, highlighting the opacity of the results. Ebner (2018) highlights that these tests contribute to financial stability by identifying key vulnerabilities. Likewise, bank risk profiles also significantly affect stress test results. Gambetta *et al.* (2019) show that banks with higher initial risk levels could face more severe impacts on their resilience, regardless of their operational efficiency. In this sense, it is critical for regulators to consider the heterogeneity among banks, as Janda and Kravtsov (2022) point out, when designing stress tests that reflect these differences.

On the other hand, factors such as institutional quality and regulatory heterogeneity between countries also influence banking efficiency. Research such as Barth *et al.* (2004) and Berger and Humphrey (1997) highlight that more developed institutional environments tend to improve efficiency due to lower transaction costs and greater transparency. In addition, Kalyvas and Mamatzakis (2014) emphasize that stricter regulatory frameworks, although necessary for stability, may generate additional costs that hinder efficient performance. Bischof *et al.* (2020) highlight how efficient judicial systems reduce the costs associated with NPLs, improving operational efficiency. Likewise, Pasiouras (2008) analyzes how bank regulation and supervision affect technical efficiency, concluding that regulatory design must balance stability and operational performance. Ultimately, institutional and regulatory characteristics are essential to explain differences in efficiency across countries. Therefore, incorporating these aspects in future research could provide a more complete perspective on how regulatory frameworks influence bank efficiency.

In this context, it is essential to pay specific attention to systemically important banks (SIBs) as they play a key role in the functioning of the global financial system, given their ability to influence economic stability and the efficiency of the banking system as a whole. Because of their relevance, they could serve as benchmarks to evaluate the efficiency of other banks in similar regulatory environments. Cecchetti and Schoenholtz (2020) point out that SIBs face increased regulatory requirements, which affect both their behavior and

efficiency. Chabot and Bertrand (2021) point out that the complexity and interconnectedness of these banks increase their exposure to systemic risk, but also allow them to benefit from economies of scale and diversification.

The present study shows that factors such as liquidity and capital ratio are key determinants of bank efficiency, suggesting that SIBs, due to their intensive supervision and higher capital requirements, could play a particular role in efficiency benchmarking. This point is supported by Lobo, Oberson and Schatt (2024), who point out that SIBs are subject to additional costs derived from more demanding audits and regulatory compliance, which may impact their operating efficiency. These higher costs, while necessary to ensure stability, could introduce significant differences between SIBs and other less regulated banks in terms of efficiency. Incorporating SIBs as a reference group in future analyses would allow us to assess how these differences influence relative efficiency in the European context.

The findings and implications outlined above highlight that it is essential to further explore the connections between efficiency, resilience and regulation in future analyses. This includes:

- Investigate whether more efficient banks are more likely to pass stress tests or withstand economic crises.
- Analyze the influence of institutional and legal characteristics on banking efficiency.
- Explore how SIBs can influence the overall levels of efficiency and stability of the financial system.

These future directions would not only enrich the existing literature, but would also provide valuable information for policymakers, allowing them to design strategies that balance efficiency and stability in the banking sector.

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