

Article



European Bank's Performance and Efficiency

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Received: 3 March 2020; Accepted: 1 April 2020; Published: 5 April 2020

Abstract: The research interest in bank profitability and efficiency is linked to the economic situation and an important issue for policymakers is to ensure economic stability. Nevertheless, managerial decisions and the environment could play a critical role in ensuring proper and efficient allocation of the resources. The purpose of this study is to understand which are the main factors that can influence the performance and efficiency of 94 commercial listed banks from Eurozone countries through a dynamic evaluation, in the period between 2011 and 2016. To achieve this aim, the generalized method of moments estimator technique is used to analyze the influence of some bankspecific characteristics, controlled by management, on the profitability as a measure of bank performance. After that, through the value-based data envelopment analysis (DEA) methodology, those factors are considered in determining the efficient banks. The results show that banking efficiency depends on set bank-specific characteristics and that the effect of determinants on efficiency differs, considering the macroeconomic conditions.

Keywords: determinants of bank performance; generalized method of moments; value-based DEA; multi-criteria decision aiding

JEL Classification: G21; G15; C33; C44; C61

1. Introduction

The research interest in bank efficiency has been recognized for a long time since banks play a central role in the economic development and growth of a country. The presence of an increasingly competitive market reinforces the great importance of assessing banks' performance to continuously improve their financial condition (Beck et al. 2000; Rajan and Zingales 1998). However, an efficient and profitable banking system is even more important for countries characterized as belonging to the civil law model, more oriented to the banking system, and less to the capital market system¹.

Due to liberalization and internationalization, competition in the financial sector has increased and, consequently, the pressure to obtain higher levels of profitability and efficiency increased as well (Meles et al. 2016). Moreover, the world banking sector, with the recent global financial crisis, had difficulty accessing financing, causing problems in terms of financial autonomy. This event has given greater importance to the banking sector concerning the global economy.

¹ For an interesting seminal paper which attempts to combine insights from the theory of corporate finance, institutional economics, and different legal and economic systems, see La Porta et al. (1998). See also Levine (2002) for a summary of the theoretical views on bank-based and market-based systems.

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Therefore, Athanasoglou et al. (2008) displayed that profitability is also important for the survival of banks, since the higher their profitability, the greater their economic capacity to cope with unfavorable situations. Besides this, efficiency is also a perception that guarantees the survival of the banks and that should be explained. This concept is often used as a synonym for productivity, however, it is a relative concept. It compares what was produced, given the resources available, with what could have been produced considering the same resources.

In this context, it is necessary to understand better which factors are determinants for bank efficiency, i.e., which variables could be more relevant for the manager's decisions to improve bank performance.

Thus, the purpose of this study is to investigate how intrinsic characteristics of banks in Eurozone countries, have an impact on bank efficiency for a period covering six consecutive years, 2011–2016. Member countries should have similar levels of economic performance, especially in the banking system, as European Union regulatory changes are designed to push the industry into the direction of a single market, especially in countries with a common currency.

In this view, the present work offers several relevant contributions to the existing literature. Firstly, the paper focuses on the banking sector, which plays a central role in the economic development and growth of a country. A profitable and efficient sector leads to more economic development. Secondly, it studies Eurozone banking, which since the financial crisis has faced major changes in terms of performance and restructuring (e.g., new capital requirements, new demands on the adequacy of directors, incentive system). Moreover, several studies have already been carried out with the aim of comparing the various economic cycles (e.g., Tsionas et al. 2015), and others helped us to identify the various moments of crisis, speculative period and deep crisis (for example, Neves et al. 2019). To that extent, we believe that our work can be considered original because it emphasizes a period not of a deep and global financial crisis, but of a sovereign debt crisis, called the eurozone crisis.

Thirdly, dual analysis is proposed, and to the best of the literature knowledge, this topic has not been studied jointly: (1) the dynamic evaluation of bank profitability uses the generalized method of moments (GMM) method (Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998), where past performance impacts present performance; (2) and the value-based data envelopment analysis (DEA) method is also used to measure banking efficiency (Gouveia et al. 2008). The GMM system provides new evidence about which bank-specific variables are important to explain banks' profitability. After that, the value-based DEA method, considering these specifics variables, identifies which banks in the dataset are the best performers. DEA is a technique for measuring the relative efficiency of peer decision making units (DMUs) doing business under the same operating conditions and allows the consideration of multiple inputs and multiple outputs in global performance evaluation. As an efficiency measure for a given DMU, the DEA uses the maximum of weighted outputs to weighted inputs.

The information that results from this type of dual analysis can be used to help the managers to identify the gaps of inefficiency, i.e., the factors in which further improvements are needed, to set future development strategies and to identify the best targets for the inefficient DMUs. Without discharge of the importance of the traditional ratio measures, it is known that each of the ratios examines only part of the activities of the DMU under analysis, leading to insufficient information on the global performance. Several authors confirm that DEA is one of the most successful operational research techniques used in evaluating banks' performance (Fethi and Pasiouras 2010; Paradi and Zhu 2013).

Finally, the results show that management decisions, reflected in the specific characteristics of the bank, are important factors explaining profitability. Moreover, the findings highlight that if bank managers want to protect their performance, they will have to improve cost management efficiency. This study can be considered as an extension to the existing literature because it focuses on the early years after the crisis (e.g., Christopoulos et al. 2019; Wild 2016). Such exposure can be relevant for managers, regulators and potential investors. The relative comparison of bank performance across Eurozone countries enables us to identify the best practices in a way that could allow policies to be

established to improve the efficiency of less efficient banks, facilitate an understanding of the impacts of constant regulatory changes on banking operations and investigate the ability of banks to realign their business with banking operations.

The remainder of the paper is organized as follows: Section 2 surveys the relevant literature on banking profitability and reviews the hypotheses to test. Section 3 is dedicated to the data and methodological framework. The results for the dynamic evaluation are presented in Section 4 and Section 5 provides some final considerations.

2. Literature Review and Hypothesis

According to Varmaz (2007) the factors that most influence the profitability of banks are market conditions regarding competition as well as service production capability. Therefore, profitability corresponds to how the company is managing its resources to create value. To measure the profitability of banks, the return on average equity (ROAE) and return on average assets (ROAA) ratios are traditionally used, because they are connected with some advantages. The ROAE provides a direct assessment of the financial return for shareholder's investment (Lee and Kim 2013) and the ROAA shows the bank's ability to generate revenue through better asset utilization (Ongore and Kusa 2013). Trujillo-Ponce (2013) argues that ROAA is perhaps the most important measure for comparing the efficiency and the operational performance of banking institutions. This is because the BROAA explains the success of the management in obtaining results with the assets that the bank holds.

The ROAE considers the contribution of all equity and off-balance sheet events, while the ROAA disregards off-balance sheet activities (Athanasoglou et al. 2008), as commitments assumed by the bank, which generate income but are not recorded in the accounts of the bank. The new challenge for bankers is focused on balance sheet management in their loan pricing discipline with strong control of operating expenses. Thus, this suggests that ROAA could be the best measure to capture bank performance.

According to extensive previous studies, the importance of factors determining the banks' performance is not new and was strengthened in the last two decades due to the fall in banking earnings, accelerated by the global financial crisis (Ghosh 2016).

These earlier studies have focused their analyses on individual country-specific studies like Athanasoglou et al. (2008); Dietrich and Wanzenried (2011); García-Herrero et al. (2009); Rumler and Waschiczek (2016), among others. Further authors already consider cross country data, for instance, Bitar et al. (2018); Dietrich and Wanzenried (2014); Nguyen (2018); Pasiouras and Kosmidou (2007); Staikouras and Wood (2004).

According to Trujillo-Ponce (2013), the determinants of bank performance could be dichotomized. First, there is a group of bank-specific determinants, resulting directly from managerial decisions, such as asset composition, capitalization, operational efficiency or size. The second group of determinants includes factors relating to the macroeconomic environment or industry specificities, such as industry concentration, economic growth, inflation, and interest rates.

In this paper, on the one hand, a model with specific characteristics of the bank, to understand which are determinant in the achievement of profitability will be considered. From there, using the value-based DEA method, it will be possible to observe how important these variables are in the definition of an efficient bank, using a cross-country comparison. Therefore, this article starts with a set of variables widely debated in the literature to estimate the bank's profitability and ends with the efficiency evaluation of banks via value-based DEA, which confirms the importance of the economic environment.

2.1. Bank-Specific Characteristic's to Determine Profitability

2.1.1. Asset Composition

The bank asset structure is an interesting bank-specific factor and the relationship with profitability is far from conclusive.

Also referred to as asset diversification, the ratio of total loans to total assets have a positive relationship in the literature, since asset diversification, e.g., hedge funds or other assets, is considered to increase profitability (Saona 2016). So, in general, loans have a positive influence on profitability, because as a bank's core business, they are a major generator of interest income (Bikker and Hu 2002).

Based on this assumption, authors, like Bourke (1989); García-Herrero et al. (2009); Saona (2016); Trujillo-Ponce (2013) refer to a positive relationship between the relative percentage of loans in the assets of a bank and its profitability.

However, other authors pointed out that ambiguous effects depending on the profitability measure are considered (Valverde and Fernández 2007; Tan et al. 2017; Trabelsi and Trad 2017), while a negative relationship between the asset structure of banks and its profitability was obtained by Bikker and Hu (2002) or Rumler and Waschiczek (2016). A large set of loans implies higher operating costs and probably the premium put on long-term interest rates (as included in the credit rate), insufficient cover for processing costs, credit losses and the cost of required capital reserves.

Consistent with this empirical evidence, the first hypothesis is stated:

Hypothesis 1: There is a relationship between the asset bank's composition and its performance.

2.1.2. Equity

There are reasons to believe that a better-capitalized bank should be more profitable because banks with higher capital to assets ratios are considered relatively safer to financial institutions with lower capital ratios. A bank with higher capital will have more flexibility to absorb negative shocks, so this positive impact on bank performance can be because capital acts as a safety net in the case of adverse developments (Athanasoglou et al. 2008; Beltratti and Stulz 2012). Also, a high level of capital can lead to a lower cost of debt, as to finance their assets, banks will not need as many interest-bearing funds. In other words, this relation would help the bank to finance its assets at the more favorable interest rates, increasing expected profitability and offsetting the cost of equity, considering the most expensive bank liability in terms of expected return (Garcia and Guerreiro 2016; Tran et al. 2016). García-Herrero et al. (2009) also argue that more capitalized banks have a high value, so they have incentives to remain well-capitalized and to engage in prudent lending. Following these arguments, it seems that banks with higher capital-to-assets ratios usually have a reduced need for external funding, which again has a positive effect on their profitability (Kosmidou 2008; Pasiouras and Kosmidou 2007). Thus, the empirical evidence indicates that the best performing banks are those who maintain a high level of equity concerning their assets. Consistent with these influences, a direct association between capital and profitability is expected, and the following hypothesis is established:

Hypothesis 2: There is a positive relationship between the equity ratio of a bank and its performance.

2.1.3. Operational Efficiency

Traditionally, the operational efficiency for the bank sector is measured by using the cost-toincome ratio (CIR), and a higher CIR reflects more cost inefficiency. To increase profitability, it is necessary to increase the efficiency of the financial institution management (Athanasoglou et al. 2008; Dietrich and Wanzenried 2011), that is, the reduction of operational costs (administrative expenses, salaries of employees, property costs) and, at the same time, to increase revenues, that could lead to a high level of bank profitability. Therefore, this ratio is usually negatively related to profitability, see, for example, Azam and Siddiqui (2012); Dietrich and Wanzenried (2011); García-Herrero et al. (2009); Garcia and Guerreiro (2016); Guru et al. (2002); Pasiouras and Kosmidou (2007), among others. Based on this assumption, the following hypothesis is considered:

Hypothesis 3: There is a positive association between the operational efficiency of a bank and its performance.

2.1.4. Size

There are a wide range of studies that associate bank dimension with profitability. The economies of scale are often cited as the reason why bank size may have a positive effect on bank profits (e.g., Diamond 1984), that is, the larger a bank, the more easily it can achieve economies of scale because, having a large dimension can increase its services with the same fixed costs, thus reducing expenses (Boyd and Runkle 1993). However, a too large bank may also incur diseconomies of scale as it will have an increase in costs, such as operational, bureaucratic and marketing expenses or inertia, thus negatively affecting the bank profitability (see, for example, Athanasoglou et al. 2008; Dietrich and Wanzenried 2011; Djalilov and Piesse 2016; Kosmidou 2008). According to García-Herrero et al. (2009), the increase in the size of the bank can also make bank management difficult due to the occurrence of aggressive competitive strategies.

Therefore, empirical research on the existence of economies of scale in banking does not come to a clear conclusion. In this context, some studies reveal a positive relationship between profitability and size (Ahamed 2017; Albertazzi and Gambacorta 2009; Altunbaş et al. 2001; Dietrich and Wanzenried 2014; Kosmidou 2008²; Petria et al. 2015), and others reveal a negative relationship (Berger et al. 1987; Pasiouras and Kosmidou 2007). Additionally, some authors like Athanasoglou et al. (2008); Bikker and Vervliet (2017) and Goddard et al. (2004), among others, found that bank size had no statistically significant influence on bank performance.

Since the literature is unclear regarding the sign of the relationship between bank size and profitability, the overall effect needs to be investigated empirically. Therefore, the following hypothesis is proposed:

Hypothesis 4: *There is a relationship between the bank size and its performance.*

3. Data and Methodological Framework

3.1. Data

The sample comprises 94 active banks listed on the main stock exchange from 19 Eurozone Countries for the period between 2011 and 2016. An unbalanced panel was constructed with the 94 European banks whose information was available for at least five consecutive years. Thus, this sample was chosen for two reasons: (i) all active banks, listed on the main stock exchange from 19 Eurozone Countries, were included as they were considered the banks with the highest volume of total assets; (ii) a necessary condition was that banks must have complete information on the variables under study, for at least five consecutive years; this condition was fundamental for the use of panel data methodology and specifically the GMM system method. We emphasize that these banks correspond to about 20% of the total assets of eurozone banks in 2016. This is important to test for second-order serial correlation, as Arellano and Bond (1991); Arellano and Bover (1995) and Blundell and Bond (1998) stated. The test for second-order serial correlation was realized because the estimation method GMM is based on this assumption (Neves 2018). The data were collected from the Bankscope database (Bureau Van Dijk's company) and it was used to test the hypotheses established in the previous section. Regarding the variables used in the model (1), since there is no consensus about which variables best explain the bank profitability, the ROAA will be considered as the dependent variable, following, for instance, Trujillo-Ponce (2013). The banks with high competition and high operating costs from increasing regulation, and fewer opportunities to raise fees to offset these costs, include an intense balance sheet management. So, in the author's opinion, ROAA could

² This author shows positive effects of size on Greek bank's performance only when the macroeconomic and financial structure variables are introduced in the model

be the best way to explain bank performance, because it is a measure which depends in a large way on the management decisions. The explanatory variables selected in this study are related to factors that are specific to banks. These variables are controlled by management and reflect the different policies and managerial decisions; consequently, they command the bank's performance (Dietrich and Wanzenried 2014, 2011; Djalilov and Piesse 2016; Guru et al. 2002). Table 1 displays more details about the selected explanatory variables.

| Table 1. Description of the explanatory variables | s. Bank-specific characteristics as determinants of |
|---|---|
| bank return on average assets (ROAA). | |

| Asset Composition | The ratio of net loans to total assets (NLTA) measures asset composition between both loans and asset portfolios. The bank asset |
|-------------------|--|
| | composition measure follows, for instance, Guru et al. (2002) or Trujillo-Ponce (2013). |
| Equity | The equity to assets ratio (ETA) is included to control for the degree of financial leverage. This is a measure of capital adequacy. The higher the ratio, the lower the risk of the bank. Capital adequacy was considered, for example, by Bourke (1989); Athanasoglou et al. (2008), or Kosmidou (2008). |
| Cost-to Income | The cost-to income ratio (CIR) represents the total expenses over total generated revenues as a measure of operational efficiency (%). The model includes CIR following, for instance, Kosmidou (2008); Garcia and Guerreiro (2016) |
| Bank Size | The bank size (SIZE) is the logarithm of the number of employees; (see, for example, Sabatier 2015 or Dang et al. 2018) |

3.2. Methodological Framework Using GMM System

Considering the ROAA as the dependent variable, and the independent variables defined before, the model (1) is established:

$$ROAA_{it} = \beta_0 + \beta_1 ROAA_{it-1} + \beta_2 NLTA_{it} + \beta_3 ETA_{it} + \beta_4 CIR_{it} + \beta_5 SIZE_{it} + \varepsilon_{it}$$
(1)

where ε_{it} is the random disturbance.

The model was estimated by using the GMM panel data methodology which has two important advantages regarding cross-section analysis. Firstly, it controls individual heterogeneity, and this fact is very important because the ROAA depends on management decisions, and this circumstance could be very closely related to the specificity of each bank. Secondly, the methodology resolves the endogeneity problem between the dependent variable and some of the explanatory variables, using lagged values of the dependent variable in levels and in differences as instruments. Thus, with this methodology, there is no correlation between endogenous variables and the error term, obtaining consistent estimates (Dietrich and Wanzenried 2014).

Therefore, the model was estimated using certain instruments, following Blundell and Bond's (1998) suggestion, when deriving the system estimator used in this paper. Note that the system GMM estimator also controls for unobserved heterogeneity and the persistence of the dependent variable. The regression was performed by using a two-step dynamic panel with equations at levels, as suggested by the same authors. García-Herrero et al. (2009) also say that the GMM system for an unbalanced panel model employs all possible instruments, and thus non-significant independent variables will be suppressed in a way that results are more effective.

There are different ways to evaluate efficiency; the parametric methods assume a pre-defined functional relationship between the resources and the products. Usually, they use averages to determine what could have been produced. The non-parametric methods, among which is the data envelopment analysis (DEA) method, do not make any functional assumptions and considers that the maximum that could have been produced is obtained by observing the most productive units. The underlying idea is to compare a set of similar units and then identify those that show best practices. Although the efficiency concept is not always accurate, in most of the cases the Pareto–Koopmans definition is usually followed. The formal definition stated by Charnes et al. (1978) says that "A unit is full efficient if and only if it is not possible to improve any input or output without worsening some of other input or output." This definition avoids the need for explicitly specifying the formal relations that are assumed to exist between inputs and outputs and there is no need to have prices or other assumptions of weights, which are supposed to reflect the relative importance of the different inputs or outputs.

It is acknowledged and confirmed by several studies that multiple criteria decision aiding (MCDA) approaches are widely used in finance (for a comprehensive review, see Zopounidis et al. 2015). The value-based DEA method developed by Gouveia et al. (2008) is a variant of the additive DEA model (Charnes et al. 1985) with oriented projections (Ali et al. 1995), in order to overcome some of its drawbacks by applying concepts from multi-attribute utility theory (MAUT). MAUT is one of the most popular analytic tools associated with the field of decision analysis (Keeney and Raiffa 1976). In the spirit of MAUT, the inputs (factors to be minimized) and outputs (factors to be maximized) are firstly converted into value functions. This transformation allows dealing with negative data, which is a difficulty in classical DEA models (Charnes, Cooper and Rhodes – CCR model and Banker, Charnes, and Cooper - BCC model).

The set of *n* DMUs to be evaluated is: $\{DMU_j: j = 1, ..., n\}$. Each DMU_j is evaluated on m factors to be minimized x_{ij} (i = 1, ..., m) and *p* factors to be maximized y_{rj} (r = 1, ..., p).

The measure of performance on criterion *c* is: $\{v_c(DMU_j), c = 1, ..., q, \text{with } q = m + p, j = 1, ..., n\}$ based on a value function (or utility function) $v_c(.)$.

Considering that p_{cj} is the performance of DMU j in factor c, the value functions must be defined such that, for each factor c the worst p_{cj} , j = 1, ..., n, has the value 0 and the best p_{cj} , j = 1, ..., n, has the value 1, resulting in a maximization of all factors. Therefore, the value functions are defined in the range [0, 1], which overcomes the scale-dependence problem of the additive DEA model.

A preliminary phase of the value-based DEA method comprises the assessment of marginal (partial) value functions on each criterion to establish a global value function. According to the additive MAUT model, the value obtained is $V(DMU_j) = \sum_{c=1}^{q} w_c v_c (DMU_j)$, where $w_c \ge 0$, $\forall c = 1, ..., q$ and $\sum_{c=1}^{q} w_c = 1$ (by convention). The weights $w_1, ..., w_q$ considered in the aggregation are the scale coefficients of the value functions and are established such that each alternative minimizes the value difference to the best alternative (bank), according to the "min-max regret" rule.

After the preliminary phase in which the factors (to be minimized and to be maximized) are converted into value scales, the value-based DEA method can be described in two phases:

Phase 1: Compute the efficiency measure, d_k^* , for each DMU, k = 1,...,n, and the corresponding weighting vector w_k^* by solving the linear problem (2).

Phase 2: If $d_k^* \ge 0$ then solve the "weighted additive" problem (3), using the optimal weighting vector resulting from Phase 1, w_k^* , and determine the corresponding projected point of the DMU under evaluation.

Formulation (2) considers the super-efficiency concept (Andersen and Petersen 1993), which allows the discrimination of the efficient units when assessing the *k*-th DMU (Gouveia et al. 2013):

$$\min_{d_k,w} d_k \tag{2}$$

$$s.t.\sum_{c=1}^{q} w_c v_c (DMU_j) - \sum_{c=1}^{q} w_c v_c (DMU_k) \le d_k, j = 1, \dots, n; j \ne k$$
$$\sum_{c=1}^{q} w_c = 1$$
$$w_c \ge 0, \forall c = 1, \dots, q$$

The efficiency measure, d_k^* , for each DMU k (k = 1,...,n) and the corresponding weighting vector are calculated by solving the linear problem (2). The optimal value of the objective function d_k^* provides the distance in terms of the difference in value for the best of all DMUs (note that the best DMU will also depend on w), excluding this from the reference set. If the score obtained in (2), d_k^* , is not positive, then the DMU k under evaluation is efficient, otherwise, it is inefficient.

In case the DMU is inefficient, Phase 2 finds an efficient target by solving the linear problem (3): q

$$\begin{split} \min_{\lambda,s} z_{k} &= -\sum_{c=1}^{n} w_{c}^{*} s_{c} \\ s. t. \sum_{j=1, j \neq k}^{n} \lambda_{j} v_{c} (DMU_{j}) - s_{c} &= v_{c} (DMU_{k}), c = 1, \dots, q \\ \sum_{j=1, j \neq k}^{n} \lambda_{j} &= 1 \\ \lambda_{j}, s_{c} \geq 0, j = 1, \dots, k-1, k+1, \dots, n; \ c = 1, \dots, q \end{split}$$
(3)

The variables λ_j , j=1,...,k-1,k+1,...,n defines a convex combination of the value score vectors associated with the n-1 DMUs. The set of efficient DMUs defining the convex combination with λ_j >0 are called the "peers" of DMU k under evaluation. The convex combination corresponds to a point on the efficient frontier that is better than DMU k by a difference of value of s_c (slack) in each criterion c.

4. Results for the Dynamic Evaluation

4.1. GMM Results

In this section, the results are discussed according to the literature review and the formulated hypotheses.

Table 2 presents the main descriptive statistics (mean, standard deviation, minimum and maximum) of the variables used in this study.

| | | | | • • | |
|---|-----------|--------|-----------|---------|---------|
| _ | Variables | Mean | Std. Dev. | Minimum | Maximum |
| - | ROAA | 0.357 | 1.376 | -13.41 | 7.401 |
| | NLTA | 53.157 | 22.691 | 0.022 | 90.91 |
| | ETA | 8.824 | 7.481 | -3.931 | 99.988 |
| | CIR | 65.01 | 19.825 | 14.654 | 287.69 |
| | SIZE | 7.988 | 1.975 | 3.611 | 12.175 |

Table 2. Summary of statistics.

The results of the estimation model are presented using a two-step dynamic panel with equations at levels. The data used are from 19 Eurozone banks for which information is available between 2011 and 2016. The resultant unbalanced panel comprises 94 banks.

Table 3 summarizes the empirical results for the profitability measure used, ROAA.

| Variables/Tests | Coefficient | Std. Error | Ζ | <i>p</i> Value | Significance Levels |
|-----------------|-------------|------------|-------------|----------------|---------------------|
| const | 5.234 | -0.5696 | 9.19 | 0.000 | *** |
| L1. | 0.0756 | 0.0145 | 5.2 | 0.000 | *** |
| NLTA | -0.0011 | -0.0055 | -0.2 | 0.843 | |
| ETA | 0.0045 | -0.0131 | 0.34 | 0.731 | |
| CIR | -0.0407 | -0.00344 | -11.82 | 0 | *** |
| SIZE | -0.2683 | -0.05915 | -4.54 | 0 | *** |
| Sargan | | | 15.052 (13) | 0.3041 | |
| Wald | | | 222.35 (5) | 0.000 | |
| AR (1) | | | -2.1307 | 0.0331 | |
| AR (2) | | | -1.3925 | 0.1638 | |

Table 3. Estimation results of the model (1).

The variables are defined in Table 1. The remaining information needed to read this table is as follows: (i) Heteroscedasticity consistent asymptotic standard error in parentheses; (ii) *, **, and *** indicates significance levels at 10%, 5%, and 1% respectively; (iii) The Sargan test with a *p* value greater than 5% shows that the instruments are valid, and the values in parentheses of the test represent degrees of freedom; (iv) The Wald test has a *p* value less than 5% which means that the joint significance and the coefficients are significant distributed asymptotically as χ^2 under a null hypothesis without significance, with degrees of freedom in parentheses. The table shows that there is no first or second-order correlation problem in the model see AR (1) and AR (2).

As expected, the negative and significant coefficient of the cost-to-income ratio shows that poor expenses management is one of the main contributors to poor profitability performance. This evidence corroborates Hypothesis 3 following, for example, Guru et al. (2002), Garcia and Guerreiro (2016), among others.

As we can see in the table, bank size is negatively related to profitability based on the view that the higher the number of employees, the higher the salary of the bank and, therefore, the lower its operating profitability. For example, García-Herrero et al. (2009) suggest that higher bank profitability could lead to more employees and less efficiency.

The results obtained are not surprising especially taking into account that the sample is characterized, in general, by being a civil law system. In fact, in the bank-based system, the economy is predominantly financed by banks, and in our sample period, the regulatory environment changed because the Eurozone was affected by the global financial crisis and the sovereign debt crisis. Under an ever-changing environment, and new rules of Basel III Risk Agreement, banks have to reinvent themselves to improve their profitability; therefore, in this context, it seems natural that bank management should use all the synergies taking advantage of economies of scale. For this reason, it is not surprising that the variables related to bank costs are the most significant in the model.

4.2. Value-Based DEA Results

The value-based DEA was applied for the evaluation of the 94 banks, for the time interval 2011–2016, considering that the factors to be minimized (inputs) and factors to be maximized (outputs) are the same considered in the GMM, attending to the negative and positive coefficient signals (Table 4). The ROAA is on the side of factors to be maximized because it is the assumed measure of profitability. Therefore, it is considered to be the "more-the-better" type of performance measure.

Table 4. The direction of optimization for factors.

| Factors to Minimize | Factors to Maximize |
|---|--|
| <i>x</i> _{SIZE} : Logarithm of the number of employees | YROAA: Return on Average Assets |
| <i>x</i> cir: Cost-to-Income Ratio | <i>y</i> ETA: Equity to Total Assets |
| XNLTA: Net Loans to Total Assets | |

Let DMU_j , j = 1,...,94 be observed in t = 1,...,6 consecutive years. Then the sample used has 6×94 DMUs (DMU_j^t). The matrices of inputs and outputs of the 564 DMUs in evaluation are $X = (x_1^1, x_2^1, ..., x_{94}^1, x_1^2, x_2^2, ..., x_{94}^2, ..., x_{94}^6, x_2^6, ..., x_{94}^6)$ and $Y = (y_1^1, y_2^1, ..., y_{94}^1, y_1^2, y_2^2, ..., y_{80}^2, ..., y_{1}^6, y_2^6, ..., y_{94}^6)$, respectively.

Considering that the value p_{cj}^t is the performance of DMU *j* in factor *c*, for the year *t*, the factors performances are linearly converted into values following the procedure: Firstly, two limits, M_c^L and M_c^U , are defined for each factor, such that $M_c^L < min\{p_{cj}^t, j = 1, ..., 94; t = 1, ..., 6\}$ and $M_c^U > max\{p_{cj}^t, j = 1, ..., 94; t = 1, ..., 6\}$, for each *c* = 1, ..., 5. Secondly, the values for each DMU are computed using:

$$v_{c}^{t}(DMU_{j}) = \begin{cases} \frac{p_{cj}^{t} - M_{c}^{L}}{M_{c}^{U} - M_{c}^{L}}, & \text{if the factor } c \text{ is to maximize} \\ \frac{M_{c}^{U} - p_{cj}^{t}}{M_{c}^{U} - M_{c}^{L}}, & \text{if the factor } c \text{ is to minimize} \\ = 1, \dots, 6; c = 1, \dots, 5 \end{cases}$$

$$(4)$$

The M_c^L and M_c^U values of the factors to minimize and the factor to maximize that were considered for all DMUs and for the interval 2011–2016 are displayed in Table 2.

The different DEA models have been widely used for performance evaluation in different practical applications, however, it is very common to find factors that have negative or zero values. For radial measures of efficiency, as the classical models (CCR and BCC), the presence of negative data is a problematical matter. The valued-based DEA overcomes this drawback by converting the performances on each factor into a value scale. Hence after being converted into value functions, all factors are to be maximized.

Value functions could also be obtained from the DMs' preferences and this may lead to piecewise and nonlinear value functions (see, for instance, Almeida and Dias 2012; Gouveia et al. 2015, 2016; and Gouveia and Clímaco 2018).

For this study, a unifying reference set for the whole period was considered, and then the optimal value difference d_k^* was computed for each bank k, in each year, making it possible to compare all of them across years.

The statistic of the scores d^* obtained with the evaluation of DMU's efficiency across the six years, using the value-based DEA method is depicted in Table 5. Attending to the results of the problem (2), the lower the value of d^* is, the better, and if d^* is negative then the DMU under analysis is efficient. The DMUs that have $d^* = 0$ are weakly efficient and the ones that have $d^* > 0$ are inefficient (Gouveia et al. 2013).

| Statistics | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|--------|--------|--------|--------|--------|--------|
| # efficient banks | 4 | 3 | 3 | 4 | 3 | 3 |
| Average of <i>d</i> * for the efficient banks | -0.069 | -0.024 | -0.026 | -0.01 | -0.014 | -0.010 |
| Std. Dev. of d^* for the efficient banks | 0.123 | 0.033 | 0.041 | 0.011 | 0.007 | 0.008 |
| Average of <i>d</i> * for the inefficient banks | 0.089 | 0.086 | 0.081 | 0.08 | 0.08 | 0.085 |
| Std. Dev. of d^* for the inefficient banks | 0.046 | 0.046 | 0.044 | 0.036 | 0.039 | 0.038 |
| Overall Average of <i>d</i> * of all banks | 0.081 | 0.0823 | 0.0774 | 0.0754 | 0.0765 | 0.0814 |
| Std. Dev. of d^* of all banks | 0.0609 | 0.0496 | 0.0486 | 0.0406 | 0.0421 | 0.0415 |

Table 5. Score statistics.

The years 2011 and 2014 are the ones that show more efficient banks, however they display the very different average of d^* . The year 2011 has the banks with the highest average score (more negative values of d^*) for the efficient banks, however, it also has the banks with the highest average of d^* for the inefficient banks (more positive values). The overall average of the bank scores, considering the different years, are better for 2011, 2012 and 2016 (>0.8).

There are three efficient banks for the remaining years, but the scores of the efficient banks are on average better for 2012 and 2013.

Probably these results are reflective of the financial help that banks were getting, gradually, after the global financial crisis (Gulati and Kumar 2016), and that impact the different Eurozone countries at different times (Wild 2016). Faced with serious economic difficulties in Greece, the European Union has adopted an aid plan, including loans and supervision of the European Central Bank. Our results are in line with Christopoulos et al. (2019) since they show that the PIIGS countries (Portugal, Ireland, Italy, Greece, and Spain) have a high degree of inefficiency, which is aggravated after the sovereign debt crisis since these countries pursued a fragile economic policy for the macroeconomic characteristics of these countries

The largest number of efficient banks in 2011 can be explained by the fact that these banks are German (3 banks) and French (2 banks), See Table 6. Data from the Statistical Office of the European Communities (Eurostat) show that in 2011, despite the severe sovereign debt crisis in some countries, Europe accelerates expansion through Germany and France. The two biggest heads of the European Union's economy announced quarterly and annualized growth data above all analysts' forecasts. Both countries had an increase in the Gross Domestic Product (GDP).

Table 6 exhibits the banks that were classified as efficient at least once in 2011–2016. The negative values of efficient DMUs are highlighted in bold. We decide to designate DMUs by banks to make it easier to follow.

| Bank | Country | <i>d</i> [*] (2011) | <i>d</i> [*] (2012) | d [*] (2013) | <i>d</i> [*] (2014) | <i>d</i> [*] (2015) | d [*] (2016) |
|--------|---------|------------------------------|------------------------------|------------------------------|------------------------------|------------------------------|------------------------------|
| Bank 1 | DE | 0.0008 | 0.0197 | 0.0011 | -0.0076 | 0.0115 | 0.0125 |
| Bank 2 | GR | 0.0761 | 0.1596 | -0.0738 | 0.1144 | 0.0886 | 0.068 |
| Bank 3 | DE | -0.005 | -0.0013 | -0.0025 | 0.0018 | 0.0059 | 0.0018 |
| Bank 4 | IT | 0.0052 | -0.0076 | 0.0078 | 0.0006 | 0.0015 | -0.0083 |
| Bank 5 | ES | 0.0097 | 0.0155 | 0.0022 | -0.0019 | -0.0074 | 0.0153 |
| Bank 6 | DE | -0.0053 | -0.0619 | 0.002 | -0.0263 | -0.0123 | -0.0029 |
| Bank 7 | MT | -0.2531 | 0.0222 | -0.0018 | -0.0023 | 0.0007 | -0.0194 |
| Bank 8 | HR | 0.0537 | 0.0678 | 0.0516 | 0.0546 | -0.0219 | 0.0394 |
| Bank 9 | AT | -0.0122 | 0.0267 | 0.0129 | 0.0318 | 0.0233 | 0.0322 |

Table 6. The scores of the banks classified as efficient at least once in 2011–2016.

The best-ranked bank, in terms of annual performance, was Bank 7, a bank of Malta. This bank has the best performance value for the return on average assets and equity to assets factors in 2011, when compared to all others in this and other years. This is likely to be related to good risk management practices necessarily implemented after the crisis. However, it also has a good performance value for the number of employees, which guarantees it to be classified as efficient in the following years. This is likely to be related to the good risk management practices necessarily implemented after the crisis (Bezzina et al. 2014).

It should be noted that, besides the Bank 7, banks that are efficient more than once, are German banks. However, Bank 4, an Italian bank, appears to be efficient as often as Spain's Bank 5.

In Table 7 the results of value-based DEA Formulation (2) are presented. Each DMU chooses its best feasible weights for factors to be classified as well as possible factors relative to the set of all DMUs (banks). That is, the efficiency scores were obtained by allowing DMUs to ignore some factors from the assessment since the DMU under evaluation is free to choose the weights associated with factors (value functions) that minimize the difference of value to the "best" DMU (bank), according to the "min-max regret" rule.

Considering the banks that were classified as efficient in 2011, it could be observed that most of them disregard y_{ROAA} and y_{ETA} ($w_{\text{ROAA}}^*=0$ and $w_{\text{ETA}}^*=0$). In the context of the economic and financial crisis, the profitability of banks suffered a significant reduction and, in some banks, fell to negative values. This may justify the fact that banks do not consider the return on average assets to be a factor in their evaluation; they are not "good" enough in it. Most of the efficient banks chose the y_{NLTA} as a relevant factor. This factor is the one that is more often chosen for the efficiency status and only four banks disregarded it from the evaluation (Bank 7 (2011), Bank 9 (2011), Bank 2 (2013) and Bank 8 (2015)). The German banks are placed at the efficiency frontier because they are the ones with the best performances associated with the risk factor and elect it as the most prevalent.

| Banks | d * | w _{ROAA} | w^*_{ETA} | w [*] _{SIZE} | w [*] _{CIR} | w_{NLTA}^{*} | N ^{er} of Times as Benchmark |
|---------------|------------|-------------------|-------------|--------------------------------|-------------------------------|----------------|---------------------------------------|
| Bank 7 (2011) | -0.253 | 0.594 | 0.406 | 0.000 | 0.000 | 0.000 | 289 |
| Bank 2 (2013) | -0.074 | 0.213 | 0.000 | 0.000 | 0.787 | 0.000 | 152 |
| Bank 6 (2012) | -0.062 | 0.000 | 0.205 | 0.000 | 0.000 | 0.795 | 9 |
| Bank 6 (2014) | -0.026 | 0.107 | 0.000 | 0.457 | 0.038 | 0.398 | 1 |
| Bank 8 (2015) | -0.022 | 0.000 | 0.000 | 0.181 | 0.819 | 0.000 | 234 |
| Bank 7 (2016) | -0.019 | 0.131 | 0.000 | 0.242 | 0.341 | 0.287 | 16 |
| Bank 6 (2015) | -0.012 | 0.000 | 0.000 | 0.133 | 0.000 | 0.867 | 0 |
| Bank 9 (2011) | -0.012 | 0.000 | 0.000 | 0.871 | 0.129 | 0.000 | 9 |
| Bank 4 (2016) | -0.008 | 0.000 | 0.000 | 0.000 | 0.896 | 0.104 | 195 |
| Bank 4 (2012) | -0.008 | 0.000 | 0.000 | 0.089 | 0.204 | 0.708 | 7 |
| Bank 1 (2014) | -0.008 | 0.000 | 0.000 | 0.000 | 0.212 | 0.788 | 6 |
| Bank 5 (2015) | -0.007 | 0.212 | 0.161 | 0.043 | 0.000 | 0.584 | 11 |
| Bank 6 (2011) | -0.005 | 0.000 | 0.000 | 0.834 | 0.132 | 0.033 | 3 |
| Bank 3 (2011) | -0.005 | 0.414 | 0.000 | 0.000 | 0.039 | 0.547 | 7 |
| Bank 6 (2016) | -0.003 | 0.089 | 0.000 | 0.826 | 0.000 | 0.086 | 0 |
| Bank 3 (2013) | -0.003 | 0.000 | 0.000 | 0.095 | 0.011 | 0.894 | 3 |
| Bank 7 (2014) | -0.002 | 0.009 | 0.000 | 0.752 | 0.165 | 0.075 | 0 |
| Bank 5 (2014) | -0.002 | 0.073 | 0.000 | 0.194 | 0.234 | 0.500 | 5 |
| Bank 7 (2013) | -0.002 | 0.000 | 0.007 | 0.463 | 0.363 | 0.167 | 1 |
| Bank 3 (2012) | -0.001 | 0.000 | 0.124 | 0.004 | 0.099 | 0.773 | 1 |

Table 7. Results of value-based data envelopment analysis (DEA) (efficiency score and optimal weights) and number of times as benchmarks, for efficient banks.

In order to find the cases where a DMU emphasizes the pure self-evaluation, in detriment to being evaluated as an organizational unit with a balanced set of factors, it is common to use a measure which consists of recording the frequency with which this DMU appears in the peer group of other DMUs (see the last column of Table 7). The higher the number of times that a DMU belongs to the linear combination that generates the projected points of other DMUs, the more likely it will be a good performance model (Charnes et al. 1984). Thus, in the set of inefficient banks, the bank that appears most often (289 times) in the linear combination that comprises the projected point (the target) is the Bank 7 (2011). This bank is followed by Bank 8 (2015), which is the second most chosen by inefficient banks. The inefficient banks choose as peers those who form the efficient frontier, the ones that have the best practices, and those who are similar to them in the way that they want to make the smallest effort on the factors towards improvement.

The solution obtained from Formulation (3) of the value-based DEA method is a proposal of an efficiency target (projection) for each inefficient bank. To attain an efficiency status, these inefficient banks must change their value in each factor by the amount indicated by s^* . Table 8 shows the results of Phase 2 only for the first 12 inefficient banks. It is interesting to observe that in the first 12 banks classified as inefficient, 11 were already classified as efficient in other years.

All the banks in Table 8, being close to the efficiency frontier, need to make a small effort on the factors towards improvement. However, all need to increase the *y*_{ROAA}. In fact, across the sample, 457

banks need to improve on this factor, considering that the same bank that has 6 years of evaluation. The positive slacks with higher average values are the ones associated with the factor χ_{CIR} , which may indicate that most important sources of inefficiency are the return on average assets and cost-to-income ratio.

Considering all the inefficient banks, the factor that most often appears with null slacks is the x_{SIZE} (186 times). However, in 564 banks, 2/3 need to improve (reduce) also in this factor to be efficient. This result is noteworthy insofar as the banks listed in the sample are also considered the largest banks in each country and throughout this article, it is possible to verify that the size of the banks is a determinant of the profitability and consequent efficiency of the banks.

| Banks | d^* | w _{ROAA} | w_{ETA}^* | w^*_{SIZE} | w [*] _{CIR} | w_{NLTA}^{*} | s _{ROAA} | s_{ETA}^* | s [*] _{SIZE} | s [*] _{CIR} | s [*] _{NLTA} |
|--------------------|-------|-------------------|-------------|--------------|-------------------------------|----------------|-------------------|-------------|--------------------------------|-------------------------------|--------------------------------|
| Bank 4 | 0.001 | 0.000 | 0.190 | 0.000 | 0.280 | 0.529 | 0.001 | 0.004 | 0.003 | 0.005 | 0.000 |
| (2014) | 0.001 | 0.000 | 0.170 | 0.000 | 0.200 | 0.02) | 0.001 | 0.001 | 0.000 | 0.000 | 0.000 |
| Bank 7 | 0.001 | 0.000 | 0.000 | 0.523 | 0.326 | 0.151 | 0.001 | 0.017 | 0.058 | 0.001 | 0.000 |
| (2015) | | | | | | | | | | | |
| Bank 1 | 0.001 | 0.000 | 0.000 | 0.000 | 0.347 | 0.653 | 0.001 | 0.013 | 0.020 | 0.344 | 0.002 |
| (2011) | | | | | | | | | | | |
| Bank 1 | 0.001 | 0.000 | 0.025 | 0.000 | 0.000 | 0.975 | 0.001 | 0.006 | 0.000 | 0.008 | 0.032 |
| (2013) | | | | | | | | | | | |
| Bank 4 | 0.001 | 0.455 | 0.000 | 0.023 | 0.116 | 0.407 | 0.001 | 0.003 | 0.011 | 0.000 | 0.000 |
| (2015) | | | | | | | | | | | |
| Bank 3 | 0.002 | 0.147 | 0.097 | 0.000 | 0.000 | 0.756 | 0.002 | 0.000 | 0.000 | 0.005 | 0.002 |
| (2014) | | | | | | | | | | | |
| Bank 3 | 0.002 | 0.000 | 0.000 | 0.035 | 0.145 | 0.820 | 0.002 | 0.005 | 0.015 | 0.000 | 0.012 |
| (2016) | | | | | | | | | | | |
| Bank 6 | 0.002 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.002 | 0.111 | 0.273 | 0.002 | 0.204 |
| (2013) | | | | | | | | | | | |
| Bank 5 | 0.002 | 0.470 | 0.019 | 0.047 | 0.000 | 0.464 | 0.002 | 0.002 | 0.000 | 0.026 | 0.008 |
| (2013) Barda 4 | | | | | | | | | | | |
| Bank 4 | 0.005 | 0.000 | 0.000 | 0.108 | 0.112 | 0.779 | 0.005 | 0.016 | 0.009 | 0.000 | 0.046 |
| (2011) Berel: 2 | | | | | | | | | | | |
| Bank 3 (2015) | 0.006 | 0.095 | 0.000 | 0.025 | 0.102 | 0.778 | 0.006 | 0.004 | 0.004 | 0.000 | 0.000 |
| (2015) | | | | | | | | | | | |

Table 8. Results of value-based DEA (Phase 2) for the first 12 inefficient banks.

In short, the post-crisis period brought the Basel III agreement, which increased regulatory costs (Anagnostopoulos and Kabeega 2019). Thus, the cost-to-income ratio contributes to the banks' inefficiency, corresponding to the adjustment that the bank had to make after the crisis, accommodating the new regulatory costs.

The bank size and the composition of their assets appear as a promoter of efficiency and profitability and this is also in line with the post-crisis period. Small banks had more financial difficulties, as a result of capital inadequacy, and a lack of financial security margin (Anagnostopoulos and Kabeega 2019). The composition of the assets also shows that in the post-crisis period, banks with fewer impairments become more efficient.

Moreover, this study shows that the number of efficient banks remains constant in the period of the sovereign debt crisis (2011–2014) and the following two years (2015–2016). This result suggest that banks restricted their funding to the economy (Kevork et al. 2018), making bank assets important for efficiency and profitability. Therefore, our results suggest that the sovereign debt crisis will have consequences in this sector until 2016 and that this will naturally condition the economy.

5. Conclusions and Further Research

Over the last two decades, several important changes occurred in the European banking industry, leading to increased competition and pressure on bank profitability.

On the whole, the findings of this work highlight that if bank managers want to protect their performance, they will have to improve cost management efficiency.

In a very difficult economic and financial environment, the challenges of banks in a bankoriented system are enormous and include low-interest rates, intense pricing competition for commercial and mortgage loans and higher operating costs, particularly related to regulatory compliance, technology, and health care. For this reason, the use of economies of scale is important, and the management decisions and specific factors of each bank, are determining factors for bank performance and efficiency.

This work points out the factors that lead to a bank being classified as efficient change, which confirms the importance of the economic environment in a way that could affect the bank performances, aside from the bank level features.

The new European regulation has been important, but the fact that in a universe of 564 DMUs (94 banks used in the value-based DEA method observed in six consecutive years) only 20 have been considered efficient shows that there is still a long way to go.

The main limitation of this study is related to the number of banks listed by country. So, for future research it would be interesting to analyze other markets and integrate institutional and ownership factors, with very different characteristics in civil law and common law countries; to compare the determinants of efficiency in the bull and bear periods also considering different external factors such cultural and market sentiment factors.

The results obtained could help managers, investors or governments to know how to improve the efficiency of their banking sector, which is the engine of the economy for civil law countries.

Author Contributions: Conceptualization, M.E.D.N. and M.D.C.G.; methodology, M.E.D.N. and M.D.C.G.; software, M.D.C.G. and M.E.D.N.; validation, M.E.D.N., M.D.C.G. and C.A.N.P.; formal analysis, C.A.N.P.; investigation, M.E.D.N., M.D.C.G. and C.A.N.P.; resources, M.E.D.N.; data curation, C.A.N.P.; writing—original draft preparation, M.E.D.N., M.D.C.G. and C.A.N.P.; writing—review and editing, M.E.D.N., M.D.C.G. and C.A.N.P.; visualization, M.E.D.N., M.D.C.G.; supervision, M.E.D.N.; project administration, M.E.D.N. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by: European Structural and Investment Funds in the FEDER component, through the Operational Competitiveness and Internationalization Programme (COMPETE 2020) [Project No. 006971 (UID/SOC/04011); Funding Reference: POCI-01- 0145-FEDER-006971]; and national funds, through the FCT—Portuguese Foundation for Science and Technology under the projects, UIDB/04011/2020 and UIDB/00308/2020.

Conflicts of Interest: The authors declare no conflict of interest.

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