



Università
Ca'Foscari
Venezia

Master's Degree programme -
Second Cycle (*D.M. 270/2004*)

in Economia e Finanza -
Economics and Finance

Final Thesis

Assessing the efficiency of
European Banks: an empirical
analysis with DEA

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Matriculation number 877479

Academic Year

2020-2021

CONTENTS

Contents	ii
Introduction	v
1. GENERAL CONCEPTS OF BANKING EFFICIENCY	
1.1 Efficiency in the Banking Sector	1
1.2 Measures of Banking Efficiency	5
1.2.1 Non-structural approach	5
1.2.2 Structural approach	6
1.3 Technical and Allocative Efficiency	7
1.4 X-Efficiency.	13
1.4.1 Neoclassic efficiency theory	13
1.4.2 X-(In)efficiency theory	15
1.4.3 Cost Efficiency	17
1.4.4 Profit Efficiency	18
1.5 Determinants of Banking Inefficiency	19
1.5.1 Incomplete contracts	19
1.5.2 Asymmetric information	20
1.5.3 Limited rationality	21
1.5.4 Opportunism	22

2. MEASUREMENT METHODOLOGIES FOR BANKING EFFICIENCY

2.1 Measurement methods	23
2.1.1 Introduction	23
2.1.2 Ratio analysis.	24
2.1.3 Parametric methods	25
2.1.3.1 DFA (Distribution-Free Approach)	26
2.1.3.2 TFA (Thick Frontier Approach)	27
2.1.3.3 SFA (Stochastic Frontier Approach)	28
2.1.4 Non-Parametric Methods	32
2.1.4.1 DEA (Data Envelopment Analysis)	33
2.1.4.2 FDH (Free Disposal Hull)	34
2.2 DEA Modelling Framework	35
2.2.1 The Concept of Decision-Making Unit (DMU) in DEA	35
2.2.2 Multiple Regression Analysis	37
2.2.3 Mathematical Approach to DEA	39
2.2.3.1 CCR Model	41
2.2.3.2 BCC Model	45
2.2.4 Application Stages of DEA	46
2.3 Determination of Input and Output Variables.	47
2.3.1 Production Approach	47
2.3.2 Intermediation Approach	48

3. LITERATURE REVIEW ON BANKING EFFICIENCY WITH DEA

3.1 Literature Review on banking efficiency	50
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4. RESULTS OF THE DEA ANALYSIS ON SELECTED EUROPEAN BANKS

4.1 Introduction	60
4.2 Inputs and Outputs used and selected models.	61
4.3 Obtained results for efficiency analysis of DMUs.	69
4.3.1 Application of MaxDEA	69
4.3.2 Application of R studio and used codes	72
4.3.3 Results of BCC and CCR model of Banks	74
4.4 Results of applied non-parametric tests to compare group of DMUs	83
4.4.1 Non-parametric tests to compare the efficiency of two groups of DMUs .	83
4.4.1.1 Mann – Whitney test	83
4.4.1.2 Kolmogorov – Smirnov test	84
4.4.2 Results of compared DMUs by regions and number of employees	85
CONCLUSION	88
BIBLIOGRAPHY	90
ACKNOWLEDGEMENT	95

INTRODUCTION

Bank efficiency has been a major question of expository and observational writing within the final 20 years. Today, the increasingly competitive environment makes it inevitable to evaluate the performance of banks, which are among the most important elements of the financial system. Efficiency in the banking sector can be defined as the banks' fulfilling their financial functions using the least number of resources. Today, when globalization is spreading intensely to the world, banks falling into the low productivity trap do not have a chance to survive.

The examination of banks' productivity and efficiency levels proceeds to be vital from both a macroeconomic and a microeconomic point of view reported by its long convention in literature. From the miniaturized scale viewpoint, managing account proficiency is pivotal, especially to move economies of Europe. From the macro perspective, the productivity of the keeping money division impacts the costs of financial intermediation and the by and large solidness of the money-related markets.

At the national or international level, one of the primary sources of economic growth and development is undoubtedly the increase in efficiency. Due to its socio-economic aspect, efficiency growth is a common denominator that encompasses the entire society for all economic decision-making units to achieve a high standard of living and banking. Nowadays, when the economy has become relatively open, and the effects of globalization are felt intensely, businesses that have fallen into the trap of low efficiency have almost no chance to survive.

In this context, it was necessary to closely monitor and measure the performance of banks in the field in which they compete, that is, the performance of banks in transforming their existing resources into output. For this purpose, efficiency analysis with the DEA method is applied to the number of employees of banks, amount of loans, business volume, capital size, and profitability.

The aim of this thesis is to conduct research about banking efficiency in the European Union, identifying the current situation of the banking sector. Data from 112 different banks operating in the European Union were used to carry out this analysis. The first chapter provides a framework on general efficiency, efficiencies, measurement of efficiency in the banking sector, financial characteristics of efficient banks, etc. In the second chapter, I presented the analysis methodology, more specifically ‘Data Envelopment Analysis’ and ‘Stochastic Frontier Analysis’ methods are examined in detail. The literature review about the DEA model on banking efficiency is investigated in the third chapter, and I put some articles about different DEA models and a table containing detailed information of these articles. The last chapter is dedicated totally to the analysis of the results. Additionally, detailed explanations are made with graphs and tables. In this fourth chapter, the input-oriented CCR and BCC models are compared in-depth, finally concluding with a comment on the results obtained by each bank and the sample as a whole.

CHAPTER 1

GENERAL CONCEPTS OF BANKING EFFICIENCY

1.1. EFFICIENCY IN THE BANKING SECTOR

In general, efficiency means to use all materials and get a product with the best-optimized form. Looking from another perspective, in the production line, something can be efficient if nothing is wasted, and along with this, all procedures are well optimized. All these optimizations are also essential for the banking sector. Benefiting from all inputs most efficiently and effectively is crucial for both banking and nonbanking institutions.

In addition, today's increasing technological developments require a competitive approach to make cost expenditures more efficient. The escalating competitive approach between non-bank financial institutions and bank financial institutions makes increasing efficiency further obligatory.

Today, efficiency is paramount to survive in the competitive field, and according to significant research, efficient banks are more competitive and cost-effective than other less efficient banks. Innovations in technology, data sharing, and globalization of contact networks increase the importance of efficiency in the banking sector. Such innovations necessitate further enhancement of productivity in the bank and non-bank financial institutions, and most of the banks offer their services through new technological means.

Today, banks that do not keep up with the times and do not apply innovations in their transactions cannot compete too much with their rivals. Even small banks tend to offer their services much faster electronically, delivering their newly released products at less cost to cope with others.

Company mergers can sometimes be seen as a chance. This is because a lot of time is known to be reduced by proportionality of financial expenditures. In this sense, consolidation offers excellent opportunities for companies to mitigate their financial expenses, make certain operational expenses at a much lower cost, and not fall behind in the competition.

In this sense, the total concept of the company, which applies to all institutions, the overall performance of efficiency, was first formulated by Edgeworth (1881) and Pareto (1927). It was later empirically applied by R. W. Shepard (1953) in the book "*Theory of Cost and Production Functions*." In the broad concept of efficiency in the economy, it is referred to as the measurement value between the inputs and outputs of the institution. In other words, this means obtaining the highest value to be reached by making maximum use of existing resources (Cvilikas & Jurkonyte – Dumbliauskiene, 2016). Efficiency by Peter F. Drucker (1963) is defined as follows: to achieve the highest possible output value, as a result, provided that you use the available inputs to the maximum.

McKinley&Banaian (2000) state in their article "*Central bank operational efficiency: meaning and measurement*" that productivity in the banking sector contributes to economic growth, increases society's well-being, and triggers permanent home development.

Let us consider the total output obtained using two inputs (capital and labour). Accordingly, we can write the production function as $Y = y(K, L, T)$, where Y is the total output, K is the capital stock (includes all machinery and equipment in the economy, factory buildings, and residences) and L is the number of employees. T indicates the state of the production technology.

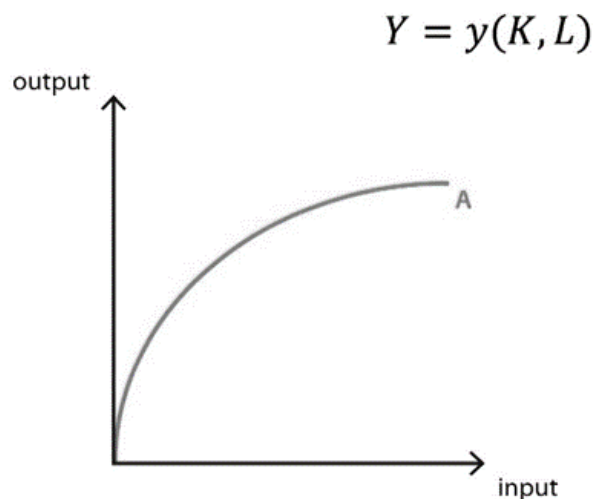


Figure 1.1. Production Function. Source: George E. Battese (1992)

How much output will be produced for the quantities of capital and labour in the total production function depends on the state of the technology. An economy with advanced technology will generate more output than an economy with primitive (back) technology using the same amount of labour and capital. What is meant by the technology, in a narrow sense, and the products that can be produced in the economy, are the production methods that can be used to produce them. When we evaluate the technological situation in a broad sense, how much production will be created in the economy depends on how well the firms' function, the behaviour and organization of the markets, the legal system and its implementation, the political environment, and similar factors.

The production function is a relationship between the quantities of inputs such as labour and capital used and the maximum amount of product that can be produced with these inputs. This relationship reflects technical efficiency only. The production function is shown in Figure (1) is based on the decline of labour, which states that the marginal product of labour decreases as the amount of labour used increases. Declining returns are shown in the form of the production function. The curve is not a straight (constant returns) or an upward curve (incremental returns) but a downward curve. While other expenses are fixed, reduced returns are explained as each worker will work with less machinery and equipment and, therefore, be less productive as employment increases. Therefore, as the amount of labour increases, output increases, but the overall rise gradually decreases. Increasing the economy's capital stock will shift the production function upwards, as this increases the amount of capital used per worker, and the marginal productivity of labour rises. The development of technology that reflects total factor productivity will also shift the production function up and make it possible to produce more labour and capital.

Banking efficiency is the most crucial topic in the financial sphere since the banking system faced several crises, big crashes, and economic turbulence. The biggest crash was the 2008 financial crisis, and finance people started to think of a more robust, sustainable, and efficient system for banking. From this perspective, efficiency, sustainability, or effectiveness are such words in terminology that financials need to catch these peak points.

Efficiency, briefly, means to catch input and output balance, more widely bank or non-bank financial institutions' ability to use current inputs most efficiently and produce maximum output. Efficiency is banks' capability to manage or to show how they handle their assets and liabilities. The Efficiency ratio is at the same time used to analyse and measure the performance

of financial services that banks offer to their clients. Moreover, we can also measure the performance of commercial and investment banks with an efficiency ratio.

The efficiency ratio for banks is non-interest expenses divided by revenue, and for banks, this type of ratio is more important. With this ratio, analysts are able to compare banks with each other, of course in the same sphere. Thus, we can write the simple but essential efficiency ratio equation:

$$\text{Efficiency Ratio} = \text{Non-interest expenses} / \text{Revenue} \quad (1.1)$$

If we take expenses as a nominator and revenues as a denominator, smaller ratio means that banks efficiency is better than its peers with bigger ratios.

We explained efficiency briefly, but there is another close terminology: effectiveness. Although efficiency and effectiveness also refer to the general performance criteria of the organization, they have different meanings. In addition to this statement, Jouadi&Zorgui (2014) have defined efficiency, as mentioned in the name, so that the efficient operation of the company is to achieve the highest possible output value in the best way by using the sum of the inputs located there. Differently, it is to make more profit by using the available resources at hand in the most optimal way.

On the other hand, effectiveness also contains maximum efficiency, but it does not consider optimizing the resources to be used; it is focused only on the outputs to be obtained. Effectiveness shows achieved goals that the companies make for their plans. Generally, all types of institutions and also banks try to make revenue from their inputs like labour force, earned liquid money, deposits, equity, and many other types of inputs, but when tough times come, and these institutions' inputs become restricted and are much less, they want to squeeze each of these inputs. From these squeezed inputs, the company gets the maximum available revenue as an output. Unlike this, effectiveness aims to reach maximum output and generate income, but without considering the optimization of input levels. Thus, bank managers primarily try to catch the optimal efficiency in the system regarding expected risk effects, but eventually, if they were not able to do it, at least put the effectiveness on the key target point. Even though in the long run, usage of inputs without optimal way may cause a decline in the general revenue and performance, in the short run, they can generate utility. Also, this will bring several problems in the future, such as agency problems, negative impact on their general profile, etc.

1.2. MEASURES OF BANKING EFFICIENCY

1.2.1. Non-structural Approach

In general terms, in the economics literature, two approaches are more prominent to measure the productivity and performance of banks or other financial institutions. These are structural and non-structural approaches. So, firstly, let's start with a non-structural approach.

The non-structural approach measures the performance levels of banks. While doing this, it makes a performance comparison between banks using various financial ratios and ratings, rates the investment and purchasing parities of the banks, or evaluates the administrative capabilities of the banks in terms of performance. As stated in its name, the non-structural approach measures the capacity of banks or financial institutions; for example, it questions how the performance ratio is related to the opening of new investment areas by combining banks' assets or linking their purchases and products.

As can be seen from all this, this approach focuses on issues related to the performance rates of financial institutions and the measurement of the quality of their administrative capabilities. Although some formal and informal theories trigger these approaches, a unifying and general perspective on performance is not presented.

At the same time, both in the structural and non-structural approaches, the reflexes and measures of performance reflect the behavioural control theory, either explicitly or implicitly. For example, for the performance equation that allows for random error, we can write a formula in this way:

$$y_i = f(z_i, \tau_i, \varphi_i, \theta_i | \beta) + \varepsilon_i \quad (1.2)$$

For the general definition of this formula, here, we can define y_i as the performance measurement of the bank. Let's define z_i as the vector of variables that catches the most essential aspects of i^{th} bank's new discoveries (for instance, the price of inputs or outputs). τ_i may be the triggering factor for technology (the ratio of total loans divided by nonperforming loans). Jensen and Meckling (1979) have added a new vector called θ_i , which is the character of the administrative system in which the i^{th} institution is located and the property rights law system, from another aspect, whether the country has an insurance system at the point of protecting the assets of foreign investors in certain situations and the degree of protection of this system to the investor and φ_i , which defines the character of the administrative form of this institution and its environmental factors, for example, it can be

included here whether the financial organization is mutual or it is stock-owned, and how many external directors are on board. The z_i and τ_i vectors differ in defining structural and non-structural approaches.

In the non-structural approach, the focus is mostly on the performance achieved in measuring the efficiency of financial institutions. Different types of ratios, such as return-on-asset or return-on-equity, measure y_i in equation (1). However, some metrics use performance measurement based on the company's market value (including the priced risk of the market).

The Non-structural approach assesses and compares banking performance by regarding new technologies in this financial area. Moreover, the non-structural approach compares peer groups by evaluating investment performance, quality of governance, or risk management of banks. The non-structural approach may explore banks characters, such as governance structure, location, environmental variables that can affect the performance. For instance, this can be like in which area bank locate if the organization type is mutual or stock-owned firm or the difference between the bank's outside and inside director in the board of directors. Although there is no exact theory for assessing these aspects, some informal and formal theories investigate the general framework of this study.

1.2.2 Structural Approach

The structural approach is more of theoretical orientation, and that is why it deals with the theoretical structure of the financial institution, its improvement concepts, and similar models. When we look at the older literature, traditional microeconomic theories are used for bank institutions (Humphrey and Pulley, 1997). And since it does not take into account the new technological developments emerging today, it is much more inadequate in calculating efficiency.

Despite this, in the new literature, banking institutions are called intermediaries. These organizations carry out sensitive financial services with the help of technology, separate the risks, and undertake significant duties in managing and directing society's social and monetary activities. And this helps to easily identify inputs and outputs in calculating the bank's efficiency (Clark, 1996).

1.3. TECHNICAL AND ALLOCATIVE EFFICIENCY

Banking efficiency's definition is still arguable that in the past several economists tried to identify and understand the efficiency, and there are different approaches that we have to learn. For the general framework, there are two approaches: the production approach and the intermediation approach.

In the production approach, banks are defined as just service producers that serve their clients in finance, such as making transactions from one client to another, giving loans, and so on. On the other side, the intermediation approach assumes financial institutions as an intermediary, as seen in its name. The intermediary's primary role is to collect money from savers and lend some part of this money to borrowers and serve all its clients in a different way, such as investment or trading. Intermediaries are in between these borrowers and savers.

In the writing of Berger & Humphrey (1997), they state that defining the financial institutions as a place that provides some documentation and transaction services and the intermediary is not fully explanatory. In some sense, the production approach can describe the branches of banks that offer these services, but in today's world, there are enough big commercial banks that accommodate all these services, such as transaction services for clients, getting funds from savers in exchange for their liabilities and investment opportunities, at the same time.

Efficiency is more crucial for banks and all other financial institutions. Obtained results show that efficient banks are more robust and resistant to upcoming troubles and crises. Efficiency has to be essential for all financial institutions in the long term regarding liquidity, cost minimization and profit maximization, improved financial services, managerial utility, etc.

Different efficiency types explain efficiency from other contexts. Scale efficiency is first mentioned by Farrell (1957). It explains the relationship between a financial institution's average production cost and volume. To measure the scale economies, a person can use the average cost function that shows how the cost function of the bank is related to the scale of operations of banks. For instance, if there is less than 1% increase in cost as a result of a 1% increase in scale, this means the firm is working with scale economies, but as a result of 1% increase in scale, if there is more than 1% increase in cost this means the firm works under scale diseconomies.

According to Farrell (1957), in the financial sphere, we can mention two different types of efficiencies: technical and allocative efficiency. Farrell is based on the work of Debreu (1951) and Koopmans (1951) in defining the efficiency measurement of a multi-input firm. Farrel argued that the efficiency of a firm includes two elements and stated that it consists of technical and allocative efficiency. Technical efficiency was defined as an indicator of a firm’s power to obtain maximum output from a set of inputs or the success of generating the largest possible output from a data input set. Again, revealing the ideal input-output component in terms of physical units in the production process and monitoring the changes in the process according to the entry of new companies into the financial sector over time is an essential indicator of sustainable competition. Allocation efficiency is defined by the ability of a firm to use production factors (such as labour and capital) at optimal rates, while input and output prices and production technology are given. We can also say that the company focuses on the most relevant production factor at the stages of supply and access to the final markets, the most suitable product that the customer group wants, at the minimum cost, and the success of selling it most affordable price. These two measures are evaluated as total efficiency or economic efficiency components, and when they are combined, overall economic efficiency is achieved. Here, it is also possible to demonstrate the technical and allocation efficiency geometrically (with graphics). Let me introduce figure 1.2 related to this:

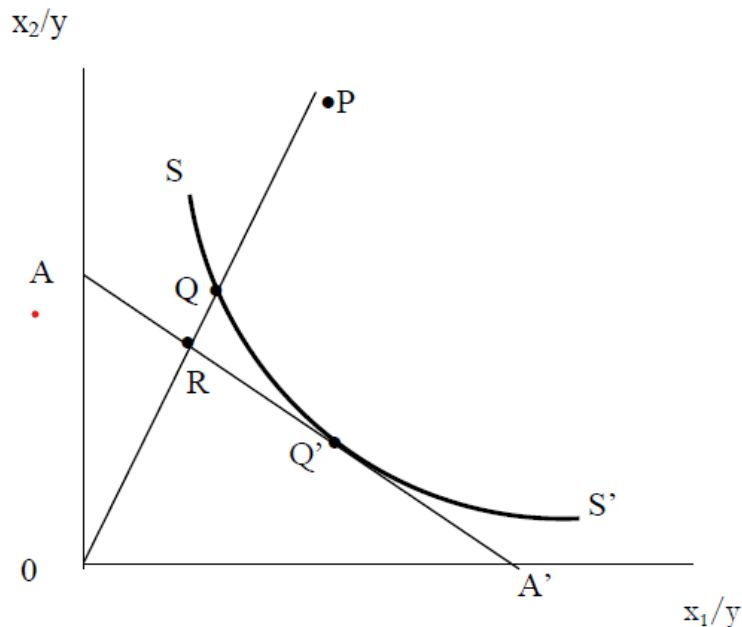


Figure 1.2 Overall, Technical & Allocative Efficiency. Source: Coelli, Roa & Batessa (1998, p.135).

The primary role of this figure is to assess and measure the cost minimization ratio. Assume that there is a bank, for instance, called ALPHA, and this bank has only two inputs which are called x_1 and x_2 . As a result of production processes, there is only one output, y , at point P. The SS' slope shown in the figure, if the bank ALPHA is totally efficient, indicates the appropriate combination of inputs that the company is able to use for the production process. The AA' slope represents the ratio of input price and depicts the different combinations of inputs for which the level of expenses has to be the same. So, the key point of this graph is, if line P crosses out the point Q', which is the intersection of the slope AA' and slope SS', this means that the cost minimization of the bank ALPHA is both technically and allocatively efficient. When we want to talk about cost efficiency, we assess the inputs that firms use and minimize the inputs to obtain the planned outputs.

However, in this figure, one can notice that the line P crosses out the slopes AA' and SS' not at the point Q' but the point Q. So, from here, we can conclude that bank ALPHA is not technically and allocatively efficient. Along with this, two types of inefficiencies may occur; technical inefficiency and allocative inefficiency. According to Farrell (1957), by multiplying the technical efficiency (TE) by the allocative efficiency (AE), we can get the general economic efficiency (EE). The formula can be written as follows:

$$EcoEFF = TE \times AE \quad (1.3)$$

Considering all of these explanations, we can say that Farrell's approach measuring efficiency technically and allocatively is input-oriented, which means reducing the input level as much as possible without changing the output level. To reach the optimal level of efficiency in the firm, by using only input-oriented cost minimization formulas or methods, the firm can't expand the output quantities forever without altering the input quantities used.

As seen in figure (1.2), if the firm uses the input quantities given by the P point to produce a unit of output, the technical ineffectiveness of the bank will be the distance QP. This distance shows how much all inputs can be reduced proportionally without any reduction in product.

This is usually indicated by the $\frac{QP}{OP}$ ratio, which indicates the reduction of all inputs to achieve technically efficient production. That is, the technical efficiency (TE) or ineffectiveness of a firm is often expressed as a percentage and is defined by the constraint $0 < TE < 1$:

$$TecEFF = \frac{OQ}{OP} \quad (1.4)$$

This value indicates the degree of technical ineffectiveness of the bank. In other words, while a constraint expresses full efficiency, values less than one reflect the degree of ineffectiveness. On the other hand, the allocation efficiency can also be calculated provided that the slope of the AA' iso-cost line and the ratio of input prices are known in Figure 1.2. Here, the allocation efficiency (AE) of a bank operating at point P is defined as:

$$AlIEFF = \frac{OR}{OQ} \quad (1.5)$$

If the process is at RQ distance, production is technically efficient but inefficient in terms of allocation. Because, although the point Q is on the isoquant curve, it is not on the equal-cost line. Therefore, the Q' point, which is effective in terms of allocation, indicates a reduction in production costs. In this case, the proportional definition of economic efficiency is:

$$EcoEFF = \frac{OR}{OP} \quad (1.6)$$

In the input-oriented efficiency measurement, the answer to not reducing the produced output or how much the input amounts can be reduced by taking the data output as a reference was sought. Another approach for banking efficiency is the number of produced services that can be increased proportionally without reducing the amount of input or data input. The answer to this question has brought output-oriented measurement to the agenda. The difference between input-oriented and output-oriented measurement methods can be explained with a simple example with a single input (x) and single-output (y) as in Figure 1.3 (a) (Coelli et al. 1998, p.137).

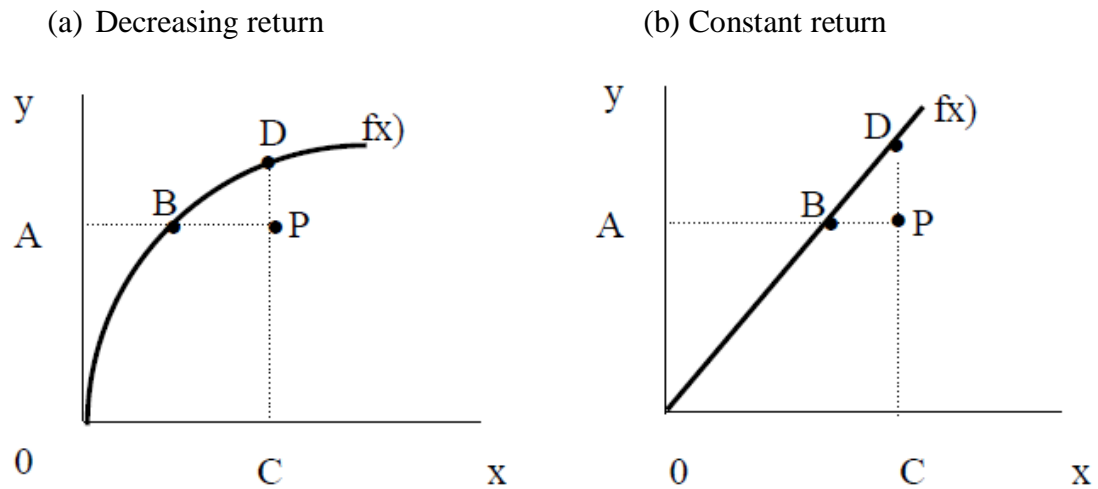


Figure 1.3. Returns to Scale: Technical Efficiency with Input and Output Oriented. Source: Recep Gök (2003)

Figure 1.3 (a) shows an example of the inefficient financial firm operating under the assumption of decreasing return to scale (VRS) at point P. While Farrell’s input-oriented measurement of technical efficiency is $\frac{AB}{AP}$, the output-oriented measure of technical efficiency will be $\frac{CP}{CD}$. In the case of constant returns to scale (CRS), input-oriented and output-oriented technical efficiency measures will be equal. Constant returns to scale situation is shown in Figure 1.3 (b). In Figure 1.3 (b), the inefficiency measure for an inefficient bank operating at point P is:

$$\frac{AB}{AP} = \frac{CP}{CD} \tag{1.7}$$

It is also possible to explain the output-oriented dimensions by considering a production process with one input (x_1) and two outputs (y_1 and y_2) (Coelli et al. 1998., p.138). This situation is analysed in Figure 1.4. In Figure 1.4, ZZ denotes the production possibilities curve, and point A denotes an inefficient firm.

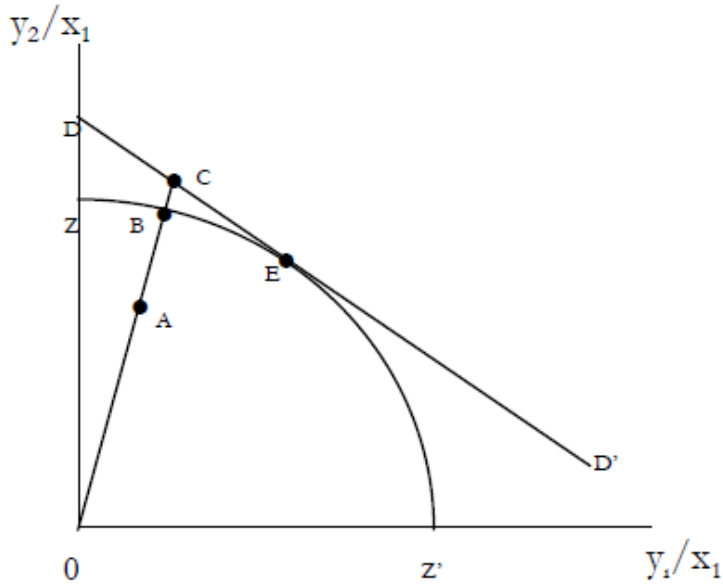


Figure 1.4. Output-Oriented Technical and Allocation Efficiencies. Source: Recep Gök (2003)

The AB distance seen in Figure 1.4 represents technical inefficiency. In other words, it is understood that the amount of output could potentially be increased without the need for additional input. Thus, output-oriented technical efficiency measurement is:

$$TecEFF = \frac{OA}{OB} \quad (1.8)$$

If we have information about the price and draw the iso-revenue curve for DD', the allocation efficiency can be calculated as follows:

$$AlUEFF = \frac{OB}{OC} \quad (1.9)$$

The general economic efficiency that can be derived from this process is formulated as follows by considering both activities together:

$$EcoEFF = (OA/OC) = (OA/OB) \times (OB/OC) = TE \times AE \quad (1.10)$$

Output-oriented efficiency, as defined above, was to get the maximum output with the least input, but what is the effective level of production that can be deduced from a defined set of activities? Which level of production is associated with competitive equilibrium? These

questions are also answered as follows. Considering the input-output matrix related to a particular production process, equation 1.11 is obtained:

$$Y = (B-A) \times X; B, A, X \geq 0 \quad (1.11)$$

If it is not possible to produce more goods than Y with the same inputs, or unless fewer inputs are used than the inputs used in the production of Y (there is no vector such as Y), output Y is effective.

1.4. X-EFFICIENCY

1.4.1. Neoclassic efficiency theory

The neoclassical theory deals with the firm or household as the main economic actor. It is assumed that firms or households behave rationally in a way that maximizes their interests, they have all the knowledge for this behaviour, and they are not under any constraints for rational behaviour (Rozen, 1985). The determinant of economic efficiency is the combination of input, price, and output (Leibenstein, 1978). In other words, according to the Neoclassical Theory, an economy achieves a balance and Pareto efficiency on the production and consumption front if input costs are minimized, firm profit and consumer benefit are maximized.

To better understand the Neoclassical Efficiency analysis and compare it with our model in the following sections, let's assume that two products such as A and B, are produced by firms A and B in the economy with a classical microeconomic assumption. Assume that the cost functions of products A and B for firms A and B are M_A and M_B . According to the Neoclassical Theory, the cost per product produced by the firm will depend only on the input costs used for these products. Considering the production function of the Neoclassical Theory, the expenditures made for the inputs (labour (I) and capital (S)) used in production will constitute the production costs of the firm. In this case, according to the Neoclassical Theory, the total cost function of the firms can be written as:

$$\Sigma M_U = M_A(S_A, I_A) + M_B(S_B, I_B) \quad (1.12)$$

In this approach, since the economic efficiency is dependent on the costs of firms producing goods A and B when the total cost of production is minimized in both firms, resources are used effectively, and efficiency in resource allocation is achieved. If we express the efficiency with θ , we can write the Neoclassical Efficacy (θ_N) function as follows:

$$\theta_N = \min \Sigma (M_A(S_A, I_A) + M_B(S_B, I_B)) = \min \Sigma M_{A,B}^U \quad (1.13)$$

On the other hand, by including efficiency in production in the model, we can explain the function as follows:

$$\theta_N = \min \Sigma M_{A,B}^U = \Sigma F_{A,B}^U \quad (1.14)$$

According to equation (3), when the total cost of the production of products A and B are minimized ($\min \Sigma M_{A,B}^U$) and this minimum total cost is equal to the total price ($\Sigma F_{A,B}^U$) of both products, the Neoclassical Efficiency criterion is met. Thus, the economy balances the production possibilities' curve by realizing the efficiency in resource allocation and production as the Neoclassical Theory assumes (Frantz et al., 1982: 865). This equilibrium situation is shown in Figure 1.3 with the E_N point on the A, B production possibilities curve.

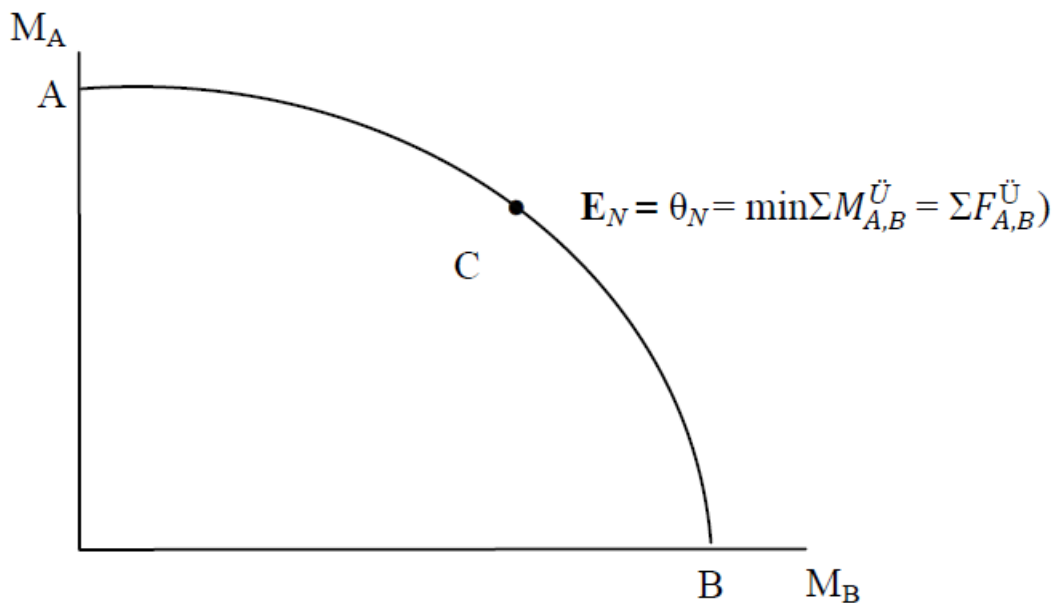


Figure 1.5. Neoclassical Production Possibilities Curve. Source: Tamer Çetin (2010)

According to the Neoclassical Theory, the only factor that will disrupt the production and allocation efficiency is the deviations from competition that break this price-cost equality. In other words, it assumes that economic activity is possible under competition and is disrupted when deviations from competition occur.

1. 4.2. X-(In)efficiency theory

X-inefficiency is that a data input amount cannot reach the maximum output for any reason (Leibenstein, 1973: 766). The approach states that in cases of X-inefficiency, the current output level obtained with the same input will be less than it should be at the potential level (Leibenstein, 1978: 17). This view implies that more production can be realized with the same amount of input used in the production process, provided that an increase in X-efficiency is achieved (Peel, 1974: 687). Contrary to the Traditional Theory, there are some fundamental reasons why a certain input amount cannot be effectively converted to a pre-determined output amount, and these determine the economic efficiency. The main difference between the two approaches arises here. While the Traditional Theory deals with the firm as the smallest decision-making unit, the X-efficiency approach puts individuals (managers and labour) working within the firm at the centre of efficiency analysis (Leibenstein, 1973). Because the obstacles to effective cooperation within the company are conflicts and differences in individual interests and goals, with this approach, it is argued that the people who are obliged to do a job and the companies-industries as a whole do not make the necessary effort to study as much as they can and search for effective information (Leibenstein, 1966: 406-407). X-inefficiencies, which occur when this effort is not sufficient, are much more critical than inefficiency in resource allocation as a social cost (Leibenstein, 1975). Therefore, the primary determinant of economic efficiency from the perspective of X-efficiency is the efforts of individuals operating in the production process (Martin, 1978: 273). Effort indicates the degree of X-efficiency. An increase in X-efficiency is due to the rise in the productivity and efforts of the employees (Peel, 1974: 687; Shen, 1985: 408).

The degree of affiliated X-efficiency depends not only on the decisions made by a firm manager for costs, production amount, and prices within the firm but also on the cooperation of managers in different departments, the company's owners and managers to supervise the workforce, interaction between firms and motivational effects arising from market conditions (Leibenstein, 1975; 1978). Thus, we can argue that the economic activity depends on

production costs, as predicted by the Neoclassical Theory, and on the level of effort made by individuals. In this case, if we call X-efficiency θ_X and effort level \bar{U} , we can express the economic activity from the X-efficiency perspective as follows:

$$\theta_X = (M_A(S_A, I_A) + (U_A^U)) + (M_B(S_B, I_B) + (U_B^U)) \quad (1.15)$$

In equation (4), U_A^U refers to the effort of individuals in the production of goods A and for goods B. According to this, the total effort level in the production of A and B goods, which is $\Sigma U_{A,B}^U$, based on equations (2) and (3), we can write the total cost as $\min \Sigma (M_A(S_A, I_A) + M_B(S_B, I_B)) = \min \Sigma$ and express equation (4) in a shorter way as follows:

$$\theta_X = \min \Sigma M_{A,B}^U + \Sigma U_{A,B}^U \quad (1.16)$$

This equation indicates that economic efficiency has two components according to the X-efficiency approach. The first part ($\min \Sigma M_{A,B}^U$) of the equation is based on the minimization of the monetary costs of the total labour and capital used in the production of goods A and B, and the second part ($\Sigma U_{A,B}^U$) states that it depends on the whole effort level of all individuals involved in the production of goods A and B. In the real world, some factors affect the level of effort other than the wages or input costs paid to the factors of production already existing in the efficiency analysis of the Neoclassical Theory. The X-efficiency approach claims that costs cannot be minimized due to these factors as in the Neoclassical Theory. Efficiency has little to do with whether the firm is competitive or monopolistic. The costs of transacting between individuals in the real world are always positive (Coase, 1960). It is complicated to define property rights and to realize effective contracts when the parties are opportunistic.

In many cases, there is uncertainty, and information is not evenly distributed between the parties. People behave selectively concerning the future and have limited rationality. In this case, we can say that the level of effort, the main element of the X-efficiency, depends on variables other than the wage paid to the labour force. If we consider that these determinants or variables depend on a variable such as γ , we can expand our model a little further. For this, we can rewrite equation (5) by including the variable γ in the model.

$$\theta_X = \min \Sigma M_{A,B}^U + \Sigma U_{A,B}^U(\gamma) \quad (1.17)$$

In this equation, the level of effort is dependent on a variable such as Y . The performance of the employees in the production process is dependent on the cost elements expressed by the Y variable. Together with the production costs, these cost elements determine the efficiency in the economy and, therefore, whether the economy will operate on the production possibilities curve or at a point outside it. Thus, the variables that determine the level of effort as a fundamental element of X-efficiency are incomplete contracts, asymmetric information, limited rationality, and opportunism, which mostly affect the effort of individuals in internal decisions or activities. Although all of these variables seem to have the same characteristics as each other, economic efficiency can be determined precisely by taking all variables into account.

1.4.3. Cost Efficiency

When analysing a production process, it is possible to calculate allocation efficiency if price info on inputs and outputs are available. Here, allocation efficiency can be measured along with technical efficiency, considering the behavioural objective function such as cost minimization or revenue or profit maximization. Two basic linear programming methods used in this measurement are needed: One of these programs is used to measure technical efficiency, and the other is used to measure economic efficiency. Such an analysis method also facilitates the measurement of allocation efficiency. The index that can be monitored for allocation efficiency is "residual," and this process is also associated with cost minimization.

Cost minimization can be solved with the pattern given below:

$$\begin{aligned}
 & \text{Min}_{\lambda, x_i^*} \quad w'_i x_i^*, \\
 & \text{constraint } -y_i + Y\lambda \geq 0, \quad x_i^* - X\lambda \geq 0, \\
 & \text{NI}\lambda = 1 \quad \lambda \geq 0,
 \end{aligned} \tag{1.26}$$

Here, w_i is the vector of input prices for the i th bank. While w_i input prices and y_i output levels data are given, x_i (calculated by linear programming) is the cost minimization vector of input quantities for the i 'th bank. Thus, total cost efficiency or economic efficiency (EE) for the i 'th bank is calculated as follows:

$$EE = w'_i x_i^* / w'_i x_i \tag{1.27}$$

Here, economic efficiency is the ratio of the minimum cost to observed cost for the i th firm. Allocation efficiency is calculated as follows:

$$AE = \frac{CE}{TE} \quad (1.28)$$

Here, while AE shows allocation efficiency, CE cost-effectiveness, and TE technical efficiency, AE is expressed as residual as required by the procedure. In other words, residuals are known as inappropriate input sets.

1.4.4. Profit Efficiency

Using an approach similar to the method above, if we consider income maximization from an appropriate behavioural assumption, allocation inefficiency can also be calculated for a mixed choice (a size made up of output components). In the case of income maximization, technical efficiency is calculated using the VRS assumed output-oriented DEA model. This process is solved as a DEA problem aimed at income maximization as follows:

$$\begin{aligned} & \text{Max } \lambda, y_i^* \quad p'_i y_i^*, \\ & \text{constraint } -y_i + Y\lambda \geq 0, \quad x_i - X\lambda \geq 0, \\ & \quad \quad \quad N^T\lambda = 1 \quad \lambda \geq 0 \end{aligned} \quad (1.32)$$

Here, p_i is the output prices, and x_i input levels are given, while p_i is the vector of output prices for the i^{th} firm. y_i (calculated with LP) is the income optimization vector of the output amounts for the i^{th} firm. Thus, total income efficiency or economic efficiency (EE) is calculated for the i^{th} firm as follows:

$$EE = p'_i y_i / p'_i y_i^* \quad (1.33)$$

Hence, EE is the ratio of observed income to maximum income. Allocation efficiency is measured by the residuals obtained using the form:

$$AE = \frac{EE}{TE} \quad (1.34)$$

When cost minimization and income maximization are evaluated together, profit maximization is achieved. Fare, Grosskopf, and Weber (1997) suggested that profit maximization can be achieved using two linear programming (LP) sets. The first of these is the profit-maximizing DEA to measure profit efficiency. The second is DEA with both input and output-oriented.

This technical efficiency measurement includes functions known as directional distance functions (Coelli, Rao. s.163).

1.5. DETERMINANTS OF BANKING INEFFICIENCY

1.5.1 Incomplete Contracts

One crucial variable to ensure an adequate level of effort is the contracts. All activities in economic life are carried out by contract. In the economic sense, a contract is an agreement between two parties to provide a mutual commitment in terms of the parties' behavior (Brousseau and Glachant, 2002: 3). The firm establishes contracts to resolve cost issues such as internal loafing, determining the effective input component, lack of information, and investment decisions. For example, in the production process, a firm makes a contract with the owners of production factors. Employees' wages, working hours, and conditions are determined through contracts. Decision-makers make decisions such as evaluating input performance, taking risk, managing money flow, and controlling employees based on the norm of the contracts. The regulations regarding these contracts are the determinants of the efficiency within the company (Coase, 1937; Alchian and Demsetz, 1972).

If there is no problem in auditing the activities of employees, execution of contracts, and uncertainty, contracts between the employer and the employee may cause Pareto efficiency. On the other hand, the lack of contracts between the employee and the employer within the company causes ineffectiveness (Newbery and Stiglitz, 1987). Neoclassical Theory takes contracts as data. According to the contract, it is assumed that a certain level of effort is understood between individuals and that the parties will always make this effort (Leibenstein, 1978: 13). Thus, it is assumed that the expected profit of the firm and the expected benefit of workers will be maximized through contracts (Newbery and Stiglitz, 1987).

Leibenstein (1966) states that contracts made between workers and management within a firm are incomplete, so there is inefficiency. Accordingly, the adequate level of labour effort can never be achieved through contracts. Under these circumstances, it is always costly to negotiate to reach an agreement for an effective contract, to search and obtain the necessary information,

to get a compromise, and finally to implement this contract (Coase, 1937; Demsetz, 1983; Joskow, 1985; Hart, 1988).

In that case, we can accept that incomplete contracts constitute a reason for reflecting the negative impact of the firm employees' efforts and for ineffectiveness. According to this acceptance, incomplete contracts are one of the variables that determine effort as a source of inefficiency.

1.5.2 Asymmetric Information

Asymmetric information problems, common in the economy, are generally one of the primary sources of economic inefficiency (Leach, 2004: 290). We can say that asymmetrical knowledge causes three fundamental inefficiencies: uncertainty, moral hazard, and adverse selection. Failure to fully distribute the information between the parties negatively affects the level of effective effort of the employees within the company by causing such problems. First of all, in cases of asymmetric information, important uncertainties arise in the predictions and the relations between the parties. Company managers are significantly affected by this uncertainty, especially in decision-making processes. Uncertainty in decisions regarding mergers or investments between companies prevents decision-makers from making the first best decision and making the most effective effort. Likewise, in internal relations, the incomplete information between the parties prevents the most effective conversion of input to output at the firm level. Especially in cases where information is incomplete and uncertainty is high, it is not possible for the manager to fully evaluate the worker's performance and make a complete contract with him. Therefore, uncertainty originating from asymmetric information causes differences in the effort level of employees, affecting the efficient distribution of resources and Pareto efficiency in the markets.

Another problem arising from asymmetric information is moral hazard. Moral hazard means that asymmetric knowledge changes people's behaviour in ways that are detrimental to society. This change of behaviour can go as far as fraud (Leach, 2004: 290). A firm manager cannot fully control workers' efforts from a firm perspective due to asymmetrical information. Likewise, if the company owner cannot fully observe the effort of the company manager, there may be a moral hazard problem between the company owner and the manager due to asymmetric information. Both situations are a principal-agent relationship. Principals are unable to fully observe the efforts of the agents due to the asymmetrical information. In this

case, employees may show hidden actions that involve inefficiencies, such as loafing, pursuing motives that are incompatible with the company's goals, and not making effective efforts. If the existence of hidden activities stems from asymmetrical information and is especially hidden by the employees, a moral breakdown occurs (Baron, 1989; Stennek, 2000).

Another negative effect that asymmetric information causes on employees' effort is adverse selection. Due to the asymmetrical information, it is almost impossible to know exactly the qualifications and intentions of the candidate or worker, for example, during job applications. The problem of adverse selection arises when the hidden qualities and intentions of the individual are not fully known, and a proposal made by this individual (job application) is evaluated. In a job application, the candidate knows best the qualifications of himself, and the employer mainly decides based on the information provided by the candidate. The decision-maker never knows how these qualities will be in an economic environment. In this case, the employer may make an incorrect choice among the candidates. The firm faces adverse selection if the process results in the selection of individuals with economically undesirable qualities.

1.5.3 Limited Rationality

Rational or "best" behaviour means that income exceeds or equals costs in all possible cases. Accordingly, the firm rationally foresees all possible future situations, realizes the optimum output level without any cost, maximizes profits, and realizes economic efficiency. However, according to the X-efficiency approach, for various reasons, people and companies do not work rationally as they normally can (Liebenstein, 1966; 1982). Because our understanding of the future will be limited due to the limited capacity of the human brain and the uncertainty of the future, all decisions are taken under limited rationality. People are myopic in terms of rational behaviour (Williamson, 2005: 46). As decision-makers, individuals cannot predict all possible results for the future (Joskow, 2005: 322). Therefore, it is certain that the predictions at the beginning of the period will generally be surprised (Rozen, 1985: 662).

Limited rationality means a cost item in production processes. Due to the limited rationality, the optimal output level cannot be fully and cost-effectively decided and realized. The firm can only approach the optimum output with its decision-making process with very good negotiation and discussion mechanisms. Apart from this, random decision-making processes can cause greater costs in the presence of limited rationality. Because firms often make decisions between the two methods, and these negotiation and discussion processes are the most effective, even

where there is an error, it becomes impossible to achieve optimum output. Under limited rationality, the process of negotiating and discussing a decision then appears as a costly input in the "production" of the decision or effort. This cost factor also complicates decision-making and prevents realizing the effective output level (Conlisk, 1996).

1.5.4 Opportunism

Company employees may prefer to act opportunistically by pursuing their interests rather than joint profit maximization (Williamson, 1979; 1985). For instance, all employees may tend to spend leisure time or slack off. Such opportunistic tendencies cause loss of output (Alchian and Demsetz, 1972), differentiation of effort level, and X-inefficiency when production within the firm is unobservable. Even if internal and external motivations are used to minimize the opportunism and ineffectiveness arising from opportunism among employees, the tendency of loafing cannot be reset (Demsetz, 1983: 381).

In the presence of Quasi or individual private "getting unearned income", especially during the contract or post-investment periods, employees may exhibit opportunism to maximize their interests rather than be compatible with the firm's interests. In the presence of Quasi "getting unearned income," employees will use their energy and time to increase their share of this unearned income rather than work at the level of effective effort. In such a case, even if the firm owner applies the incentives to eliminate the unearned income sharing conflicts, the firm will not reach the optimal level by excluding these opportunism costs (Ellingsen, 1997: 583). In this kind of opportunism, what is aimed at the beginning of the term cannot be achieved at the end of the term (Demsetz, 1983). For example, the targeted investment level cannot be reached due to opportunistic deviations in the effort levels of employees. Opportunism, then, can hinder the realization of effective contracts and cause high costs, triggering economic inefficiency.

CHAPTER 2

MEASUREMENT METHODOLOGIES FOR BANKING EFFICIENCY

2.1. MEASUREMENT METHODS

2.1.1 Introduction

Concepts such as efficiency and productivity have always been and will continue to be important in our world of limited resources. There is a great interaction between efficiency and competition. Efficiency becomes vital in situations of competition.

The importance of efficiency becomes more evident in times of crisis. Firms in the economy have to learn to work efficiently, that is, to be as less wasteful as possible in their use of inputs, in order to survive the melting of profit margins created by adverse changes in competition or environmental factors. Removal of barriers to entry to the markets opens the way for companies that work efficiently, and as a result, societies can access cheaper products.

Effective and efficient operation is also important for the financial sector and banking system, which are critical in economies, for similar reasons. However, the efficient functioning of the banking system is of particular importance for the economy. This difference is due to the fact that the banking sector assumes the function of financial intermediation, which determines the resource distribution, unlike other economic sectors. In this respect, the banking system has a central position in the economic development of countries. It is not possible to talk about the efficiency or productivity of a banking system that cannot turn savings into productive investments. For these reasons, efficiency and productivity criteria should be examined in order to make a performance analysis of a banking system.

Before moving on to efficiency and productivity measurement methods, it is necessary to mention the services that these methods offer especially to financial market regulators. It is extremely important for regulators to be able to identify and model the system and obtain

quantitative measurements of its performance so that they can predict the possible effects of the political decisions they will implement on the system and analyse the results of previous applications. For example, regulators need to have analysed and interpreted empirical work on how brokerage services are affected as a result of increases and decreases in operating costs as a result of mergers and acquisitions or capital ratio increases. Similarly, it is important for the system in general to predict firm downturns as a result of the management inadequacies observed by the regulators in the system and redistribute control resources in a way that can eliminate the deficiencies. Regulators want to see through quantitative measurements how regulations such as interest rates imposed on financial institutions, insurance premiums, measures applied to hedge, geographic area constraints in which organizations can operate and the types of products they can provide affect the performance of organizations. If the regulatory authorities do not have such information, it is highly likely that the policies they will implement will undesirably increase system costs, reduce the quality and quantity of financial services provided, and increase systemic risk.

Not only regulatory authorities, but also companies that provide financial services need to measure their performance, compare them with other companies in the sector, and identify their efficient and inefficient units within the company. As a result of these efforts, banks can show their active branches as an example to their inefficient branches and ensure the transfer of knowledge and experience between branches.

Efficiency measurement methods can be divided into three groups as ratio analysis, parametric and non-parametric methods. All of the methods included in these groups have their own advantages and disadvantages.

2.1.2. Ratio analysis

The ratio analysis method is applied by monitoring a ratio formed as a result of the ratio of a single input and a single output over time.

Although it is widely used for its ease of application and interpretation; this method has a major drawback. It is not possible to make decisions by looking at a single ratio and to understand the efficiency of the bank or branch, especially in decision-making units that contain many inputs and outputs such as the banking system. In general, more than one ratio is examined at

the same time to eliminate this drawback. However, this time, problems arise such as not being able to make a meaningful group of the analysed ratios, and therefore whether they can be evaluated together or not. In cases where all inputs and outputs cannot be transformed into a common unit, inputs and outputs subject to efficiency measurement process have to be evaluated separately. This often leads to results that are impossible to interpret. Since the ratios alone do not make much sense, their evaluation does not change the situation (Cingi, Armagan, 2000, p.11). If the number of inputs and outputs increases, the analysis becomes even more ineffective.

In ratio analysis, "temporal ratios" are used to reveal the changes between periods or years. Instantaneous ratios examine the relationship of two separate items in a financial statement as of a certain date. For normative ratios, there is usually a predetermined well-performing target ratio. By comparing the absolute value of the ratio and the target number, an opinion can be drawn about the situation. While performing ratio analysis, it is necessary to examine the level of a certain ratio together with its development over the years and to make a comparison according to similar bank groups in terms of fields of activity, types of banking transactions and bank sizes (Shenver,1988, p.13- 14).

As stated above, there are many inputs and many outputs in the banking system. However, there is no agreement on what these inputs and outputs are. According to some approaches, a variable accepted as an input can be accepted as an output in another approach. Also, variables accepted as input and output are not homogeneous in terms of units. These drawbacks should be taken into account in the evaluation of studies that have been analysed for efficiency using the ratio analysis method. I will explain the determination of inputs and outputs in third section.

2.1.3. Parametric methods

Parametric and non-parametric methods actually constitute a group called the frontier approach in efficiency and productivity measurement. However, the two method groups have profound differences. Basically, frontier approach analyses are complex benchmarking methods (Berger and Humphrey,1997, p.1). Frontier approach analyses differ by the efficiency frontier shape, the presence of random error, and the distribution assumptions made to distinguish between inefficiency and random error if there is a random error (Bauer et al., 1998, p.2). These

methods also differ on whether the measured efficiency is technological or economic. While non-parametric Data Envelopment Analysis (DEA) studies are generally concerned with technological efficiency, parametric Distribution-Free Approach (DFA), Thick Frontier Approach (TFA) and Stochastic Frontier Approach (SFA) are generally concerned with determining economic efficiency (Bauer et al., 1998, p.7).

In parametric methods, there is generally a set of observations and assuming that the best performance in this set is on the regression line (efficiency frontier), observations that do not deviate from this line are efficient; Other observations that fail according to this observation are defined as inefficient. It should be noted that failure means high cost at the same level of output or low output at the same level of input and the observed production units are assumed to be homogeneous. Also, the method assumes that there will always be a random error. Fully effective observations are already observations with zero error. Therefore, the ineffectiveness of an observation can only be decided after the measurement errors have been eliminated.

Parametric methods (SFA, TFA and DFA) have a disadvantage as they use the frontier approach, which has a more structural shape than non-parametric methods. However, parametric methods are advantageous in that they allow random error. Because these methods are more successful in finding out the measurement errors. The biggest challenge facing parametric methods is how to distinguish random error and inefficiency. Parametric methods differ from each other by the distribution assumptions they use to make this distinction. Thus, it turns out that deviations from the efficiency frontier in parametric methods consist of two elements such as inefficiency and random error, and it is also of great importance to distinguish these two error components. These methods differ from each other by assumptions about how these two error elements are distributed. The rationale for these methods is briefly discussed below.

2.1.3.1 DFA (Distribution-Free Approach)

These criticisms of the stochastic method caused the DFA method to come to the fore. This method, as the name suggests, assumes that under certain constraints the error terms and their components (ineffective observation and random error) can have any distribution. However, in the DFA method, which can be used under the presence of panel data, the long-term core

efficiency of each firm is stable, and measurement errors are also close to zero in the long run. These assumptions are valid provided that ineffective observations are positive.

If over time the productivity of a firm (assumed to be constant in the long run) changes significantly due to technology, changes in regulation, volatility of interest rates, or other similar factors, then the deviation of each unit whose efficiency is measured is taken into account. When this technique is applied to banks, observations with too low and / or too high error terms are excluded. This process is called truncation.

DFA also applies a functional form for the cost function, such as SFA and TFA methods. As mentioned before, DFA does not make an assumption on the distribution of efficiency as in the SFA method, and as in the TFA method, the whole group of firms does not count random error and inter-group deviation as inefficiency.

2.1.3.2 TFA (Thick Frontier Approach)

The TFA method differs from SFA and DFA methods, especially with the assumptions it makes on distribution. The assumptions of SFA and DFA methods regarding the distribution of inefficiency and random error elements that make the difference between observed values and assumed values constitute the main difference between the two methods. On the other hand, there is no assumption regarding the expected distributions of these two elements in TFA method. It is assumed that only the largest and smallest values of the differences between observed and expected values constitute the random error, while the remaining values constitute the ineffective observations. Thus, the TFA method becomes an unsuitable method for estimating the efficiency of a single production unit. However, it is used to calculate the general efficiency level. The elimination of the highest and lowest values by counting random errors in the TFA method is actually similar to the truncation process in the SFA and DFA methods.

TFA also uses the same functional form for the boundary cost function like SFA, but is based on regression analysis of observations that visibly perform the best. The parameter estimates obtained from this analysis are then used to obtain best practice cost estimates for all firms. The quarter created by the lowest cost banks is considered to be above the average performance and creates a thick frontier. As generally applied, TFA assumes that deviations from estimated

performance values in the top and bottom mean cost quarters represent only random error, while deviations between the top and bottom mean cost quarters represent only inefficiencies and a special kind of combined error. Thus the measured inefficiencies are buried between the estimated top and bottom cost quarters.

As with SFA, the efficiency levels determined by TFA can also be discussed because they are based on assumptions that are not firmly grounded (such as firms in the lowest cost quarter forming the thick line of active firms). However, again as with SFA, there is reason to be optimistic about the efficiency ranking TFA has produced. Because efficiency ranking is determined by the remainder of the cost function after controlling input prices, output quantity and possibly other factors.

There seems to be no agreement in the efficiency literature as to which of the three methods listed above is better and more convenient than others. On the contrary, there are criticisms directed at the common points of these three methods. It is possible to gather these criticisms around two main arguments.

Since these methods establish a functional relationship between explained variables such as cost, profit and production and explanatory variables such as input, output and environmental factors, they make some behavioral assumptions that will make this relationship possible. If these assumptions are wrong, obviously the model's findings will become controversial.

2.1.3.3 SFA (Stochastic Frontier Approach)

SFA, also known as the econometric approach, with variables explained such as cost, profit and production; establishes a functional relationship between explanatory variables such as input, output and environmental factors and also allocates room for margin of error in the model. In this technique, the above-mentioned random error and ineffective observation must be separated from each other. It is clear that the results of the model will not be reliable without understanding how much of any observation deviates from the best case is random error and how much is ineffective observation. These two elements are usually distinguished by assuming that they have different distributions.

SFA applies a composite error model (usually semi-normal) based on the assumption that ineffective observations have an asymmetric distribution (usually standard normal) (Bauer et

al., 1998, p.11). That is, the error term given in the model (the model is set up as a cost function) is expressed as “ $e = m + v$ ”. Here m represents zero inefficiency and has semi-normal distribution, while v represents random error and fits normal distribution. This is because inefficiencies will not reduce the cost, so they must have a rounded distribution. On the other hand, since random error can act in both an upward and downward direction of the cost function, it must have a symmetrical distribution. Bauer et al. (Bauer et al., 1998, p.12) argue that these assumptions are unfounded and can cause error in the analysis of firm activities. For example, the semi-normal distribution assumption about inefficiencies (m) causes most firms to concentrate at the efficiency frontier. Also, there is no theoretical reason why inefficiencies are not distributed more symmetrically like random errors. In some studies using the DFA method, it has been determined that the inefficiencies are distributed more symmetrically than semi-normal.

Stochastic Frontier Analysis (SFA) was proposed by Aigner, Lovell, Schmidt (1977), Battase and Corra (1977), Meusen and Van den Broeck (1977) in an interconnected and concurrent manner. Schmidt (1985) and Lovell (1993) consider efficiency prediction methods in two categories. The first is that the production functions are handled with parametric and non-parametric methods, while the second is related to the fact that the model that concerns the deviation of the business from the production frontier is stochastic or deterministic. Later, Van den Broeck, Koop, Osiewalski and Steel (1994) developed the Bayesian approach to get rid of the constraints of stochastic and deterministic models (Dudu, 2006: 46; Atılgan, 2012: 30). Stochastic frontier analysis can be carried out in two ways: production and cost.

The frontier function actually expresses the value of the function in the absence of inefficiency. Since it is the production function mentioned at this point, the production functions considered show the frontier of that production relationship (Tutulmaz, 2012: 113). The production function used in stochastic frontier analysis is shown below:

$$y_i = x_i\beta + \varepsilon_i \quad (2.1)$$

$$\varepsilon_i = v_i - u_i \quad (2.2)$$

In this equation, y_i denotes the output amount of the i^{th} decision unit, β indicates $(K \times 1)$ dimensional input vector parameters to be estimated, and x_i denotes $(K + 1)$ dimensional input line vector. There are two error terms in the equation, v_i and u_i . The stochastic production

frontier model assumes that ε_i arises from two independent variables composed of u_i . v_i refers to statistical noise, measurement errors, random factors outside of business control, and random variables not included in the production function. u_i is a random variable representing inefficiency, non-negative. The output variable is limited to the top by the random variable $\exp(x_i\beta + v_i)$. The ratio of the observed output of the i^{th} firm to the potential output shows the technical efficiency of that firm. The technical efficiency marked by TE is expressed as in equation (2.3):

$$y_i = f(x_i; \beta) * TE \quad (2.3)$$

$$TE = \frac{y_i}{f(x_i; \beta)} \quad (2.4)$$

Technical efficiency becomes 1 only when y_i reaches its maximum level, in other cases, technical efficiency is less than 1 since there is a deficiency in the observed output.

In equation (2.3), the production frontier $f(x_i; \beta)$ is deterministic. In other words, the part that can not be obtained from the maximum producible output is expressed as technical inefficiency. Such a definition ignores that output may be affected by random shocks beyond the manager's control. To include random shocks in the analysis, the model is rewritten as in equation (2.5):

$$y_i = f(x_i; \beta) * \exp(v_i) TE_i \quad (2.5)$$

In this equation $[f(x_i; \beta) * \exp(v_i)]$ is the stochastic production frontier. The stochastic production frontier consists of two parts: the $f(x_i; \beta)$ and the deterministic part that includes the effect of random shocks on each producer. If the production frontier becomes stochastic, the technical efficiency is as shown below:

$$TE_i = \frac{y_i}{f(x_i; \beta) * \exp(v_i)} \quad (2.6)$$

The stochastic production frontier function is expressed as in equation (2.7) by including the random error v_i expressing the statistical noise in the model (Coelli et al., 2005: 242):

$$\ln y_i = x_i\beta + v_i - u_i \quad (2.7)$$

Random error v_i can be positive or negative. For this reason, stochastic frontier outputs may vary in the deterministic part of the model $\exp(x_i\beta)$. The model in Cobb-Douglas form, which is one of the most applied models in stochastic frontier analysis, is expressed below:

$$\ln y_i = \beta_0 + \beta_1 \ln x_i + v_i - u_i \quad (2.8)$$

$$y_i = f(\beta_0 + \beta_1 \ln x_i + v_i - u_i) \quad (2.9)$$

$$y_i = \underbrace{f(\beta_0 + \beta_1 \ln x_i)}_{\text{Deterministic component}} * \underbrace{\exp(v_i)}_{\text{Random error}} * \underbrace{\exp(-u_i)}_{\text{Inefficiency}} \quad (2.10)$$

Equations (2.8), (2.9) and (2.10) show different ways of expression of stochastic production line in Cobb-Douglas form. The output that is not inefficient in the production function, realized at the production frontier and defines the effective state can be shown as follows:

$$q_i = \exp(\beta_0 + \beta_1 \ln x_i + v_i) = \exp(\beta_0 + \beta_1 \ln x_i) * \exp(v_i) \quad (2.11)$$

Technical efficiency is defined in equation (2.12) as the ratio of observed output to the maximum output limit that can be produced:

$$TE = \frac{q_i}{q_i^*} = \frac{\exp(\beta_0 + \beta_1 \ln x_i + v_i - u_i)}{\exp(\beta_0 + \beta_1 \ln x_i + v_i)} = \exp(-u_i) \quad (2.12)$$

In Figure 2.1, two manufacturing companies, A and B, are discussed. Input values are shown on the horizontal axis and output values on the vertical axis. Firm A uses input x_a to produce output q_a while firm B uses input x_b to produce output q_b . The production frontier of Firm A is above the deterministic part. This is because the noise effect ($v_a > 0$) is positive. On the other hand, firm B's output limit is under the deterministic part. The reason is that the noise effect is negative ($v_a < 0$). In addition, the level of observed output of firm A is below the deterministic limit. Because the sums of noise and inefficiency effects are negative (Coelli et al., 2005: 243).

Despite the potential problems encountered in measuring efficiency levels, the Stochastic Frontier Approach method is always successful regardless of what distribution assumptions are made in the efficiency ranking of firms. This feature increases the attractiveness of the SFA method for regulatory purposes.

The main criticisms of the method are related to the assumptions of distribution as discussed above. There are many studies that have found that inefficient observations show a close distribution to the normal distribution or that the random error does not show a normal distribution.

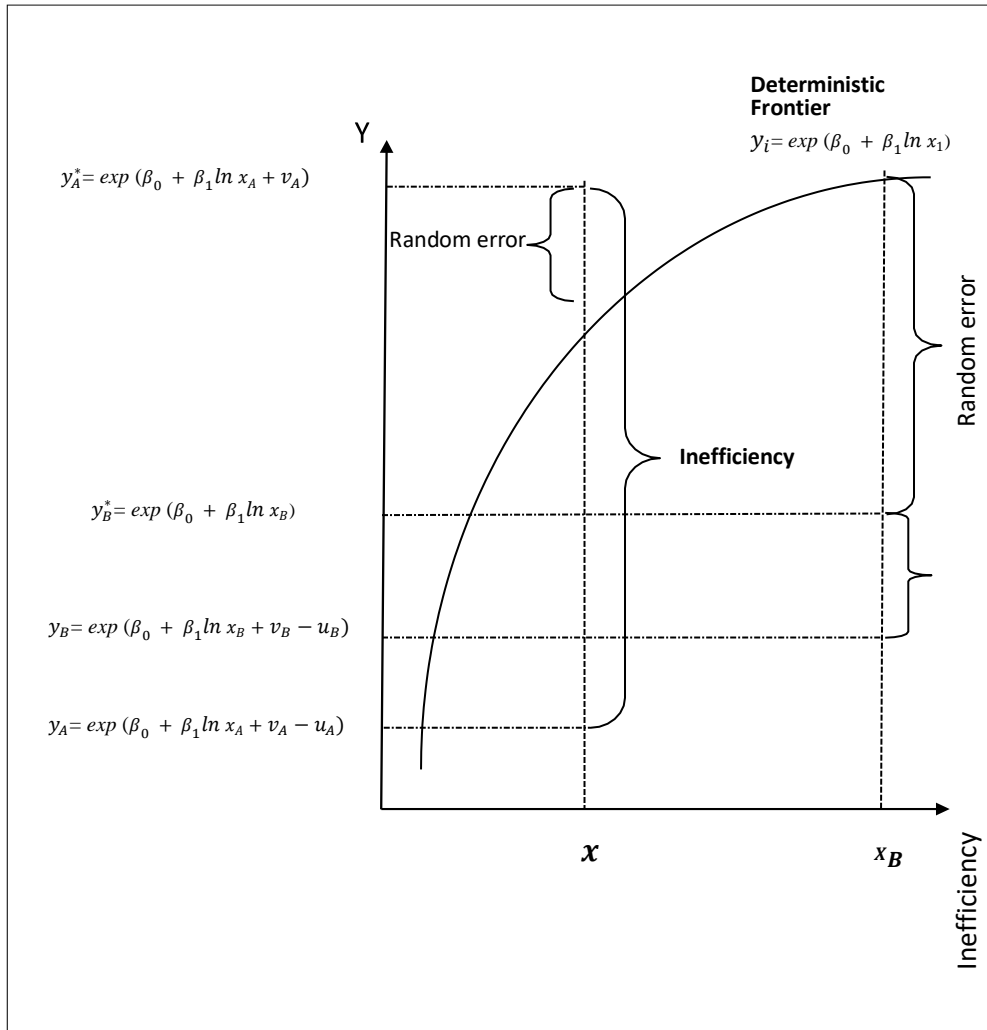


Figure 2.1 Stochastic Production Frontier. Source: Coelli et al. (2005, p. 244)

2.1.4. Non-parametric methods

Non-parametric methods try to measure the distance from the efficiency frontier using linear programming based techniques (optimization under constraint). These methods are relatively advantageous in that they do not have to enter behavioral assumptions about the structure of the production unit as in parametric methods. In addition, these methods have an additional advantage of using more than one explanatory variables. On the other hand, since they do not contain a random error term, data and measurement errors transfer errors caused by chance or other reasons to the model and may incorrectly determine the efficiency limit.

The most widely used of these methods is the DEA (Data Enveloping Analysis) method proposed by Farrell and Fieldhouse (1962, p.252-267.) and developed by Charnes, Cooper and Rhodes (1978, p.429-444). Another method is called FDH (Free Disposal Hull).

2.1.4.1 DEA (Data Envelopment Analysis)

The most commonly used method among non-parametric methods is DEA method. This method compares the production units that are assumed to be homogeneous among themselves. After accepting the best observation as the efficiency frontier, other observations are evaluated according to this most efficient observation. Therefore, the efficiency frontier in the DEA method is not a default situation; it is an observation that takes place. Since the efficiency frontier is determined in this way, random errors are not used in this method.

For the DEA method, it is necessary to open a slightly broader bracket in addition to this general information. Because, DEA has some advantages compared to parametric methods in efficiency measurements, especially in the field of banking. The advantages of the DEA method over parametric methods can be briefly listed as follows:

- It is possible to use many inputs and outputs in DEA models. (This feature is very important especially for the banking sector, which has a large number of inputs and outputs.)
- DEA method does not have to construct a functional relationship between input and output as in parametric methods. (In real life, it seems quite problematic to construct such a relationship based on a single output, and if this relationship is established incorrectly, the whole model will be affected).
- It compares the units with the same quality (homogeneous) among themselves. Perhaps the assumption that the units of production compared in the real sector are homogeneous is debatable; but when it comes to the banking sector, this assumption becomes relatively meaningful.
- Inputs and outputs can be expressed in very different unit values. (In terms of physical production, monetary size, even ratios).

Besides these advantages, which are especially important for the banking sector, DEA method has some drawbacks. These drawbacks can be listed as follows:

- Since there is no place for random errors in DEA method, the measurement methods and noise in the data cannot be eliminated and therefore the problems related to the data are significantly reflected on the results. Suppose it indicates a better performance and is well above the average of the data set. If this data is not extracted, it will set the efficiency frontier and all the remaining data (perhaps while it should appear at average efficiency) will appear quite inefficient. There is no sure way to fix this error. For this reason, the person conducting the research should know very well the data set he has dealt with, the reasons affecting this set, the conditions specific to the time interval taken, and if necessary, he should extract his data.
- The efficiency figures found even in the most problem-free research conducted with DEA method are relative. There is no absolute measure of efficiency. Therefore, the coverage of the data set gains special importance. For example, let's assume that a study has been conducted to examine the efficiency of public banks and that public banks are quite inefficient compared to private or foreign banks. As a result of the research, one of the state banks will be fully efficient and most of them will be at average efficiency. Perhaps it is possible to add the data of a unit that is assumed to be active as an indicator to solve this problem, but selecting this indicator is equally problematic.
- DEA is not very suitable for statistical hypothesis testing since it is a nonparametric technique. Therefore, testing the results of the model is more complicated than for parametric methods.

In the second section, I will explain more in detail the mathematical foundations and properties of data envelopment analysis used in this study.

2.1.4.2 FDH (Free Disposal Hull)

The Free Disposable Hull model is a special case of data envelopment analysis and does not include the edges joining the corners of the DEA model in the production set. Instead, the observation points and the area covering their southeastern portions are located within the production cluster (Berger and Humphrey, 1997, p.5-6). Thus, the ladder-shaped frontier of the generated production set and the distance between the production set elements will determine how efficient each activity is relatively. Inefficient production units are dominated by efficient production units. Here, sovereignty should be understood as the ability to produce more with less input. In another definition, effective production activity is an input - output pair over

which other production activities cannot be dominated. FDH produces larger average efficiency estimates since it covers either the neighboring or inner part of the DEA model (A. Ertugrul and O. Zaim, 1996, p.48-49).

2.2. DEA MODELLING FRAMEWORK

2.2.1 The concept of decision-making unit (DMU) in DEA

Today, the increasingly competitive environment makes it inevitable to evaluate the performance of banks, one of the most important elements of the financial system (Ecer, 2013: 171-179). Today, when globalization is spreading intensely to the world, banks falling into the low productivity trap do not have a chance to survive (Yolalan, 2001: 4).

In this context, it is necessary to closely monitor and measure the performance of banks in the field in which they compete, that is, the performance of banks in converting their existing resources into output. For this purpose, efficiency analysis with DEA method is applied on the number of employees of banks, number of branches, business volume, capital size and profitability.

Since DEA is a relative efficiency measurement technique, appropriate decision-making units should be determined in order to make an analysis. Which decision unit is suitable for the study depends on the subject that constitutes the content of the study. The decision units to be selected can be any production unit that converts inputs into outputs. These decision units must be sufficiently similar to each other in terms of their production, transform similar inputs into similar outputs, and operate in similar environments. So DMUs must be homogeneous. The choice of decision-making units is affected by two types of restrictions; organizational, physical and regional constraints that affect the selection of individual units and the time periods used when analyzing the efficiency of decision-making units. It should be kept in mind that the prolongation of the periods will not reflect the important changes that may occur within themselves, and short periods will not provide sufficient information about the activities of decision units.

The meaningful and reliable results of efficiency measurements also depend on the number of decision units selected. In addition to those who argue that the required number of units should be at least three times the number of inputs and outputs in order to measure the efficiency of the selected decision units in a healthy way, there are also those who argue that this number is at least twenty in line with the experiences obtained from the studies. From here, we can say that when we create a large unit set, the relationship between inputs and outputs in the set is determined correctly (Bakırcı Kutlar, 2018: 183). The decision units chosen should have a homogeneous structure in terms of size.

Efficiency analysis of homogeneous units with similar production technologies and using the same input-output combinations ensures healthy results. When scale sizes are unbalanced, large scale decision units can be designated as inactive units. In order to make the scale sizes homogeneous, some corrections may be required by measuring inputs and outputs in different ways. Otherwise, banks that should be efficient when unequally sized banks are included in the research may not be found efficient.

The inputs and outputs used in DEA are chosen with great care as they will form the basis of comparing the decision-making units in the study. However, adding too many inputs and outputs to the model reduces the ability of DEA to distinguish between efficient and inefficient.

Discriminant analysis, which is a multivariate statistical method, has two main objectives, separation and classification. A model developed with linear multivariate discriminant analysis is the linear combination of variables that provide the best distinction between successful and unsuccessful groups (Yakut and Elmas, 2013: 269-270). Due to the relative nature of DEA, removing a unit may cause the relative efficiencies of the remaining units to appear higher than they are (Aslankaraoglu, 2006). Likewise, missing, incorrect or extreme data among the data will affect the efficiency score to be obtained as a result of the analysis, such data should be determined and excluded from the study (Ozata, 2004: 101). The graph below shows the Efficiency Frontier of DEA. It is observed that active units constitute efficient frontier and envelop other inactive units. In DEA, no assumptions are made regarding the inputs and outputs functional forms. Instead, a set of production possibilities is created based on observed inputs and outputs. We see that decision-making units produce the most output with the least input form the efficient frontier. *A, B, KI, C* and *D* are efficient decision-making units. The line segments that combine these decision units form the efficiency frontier”(Yucel, 2017: 75)

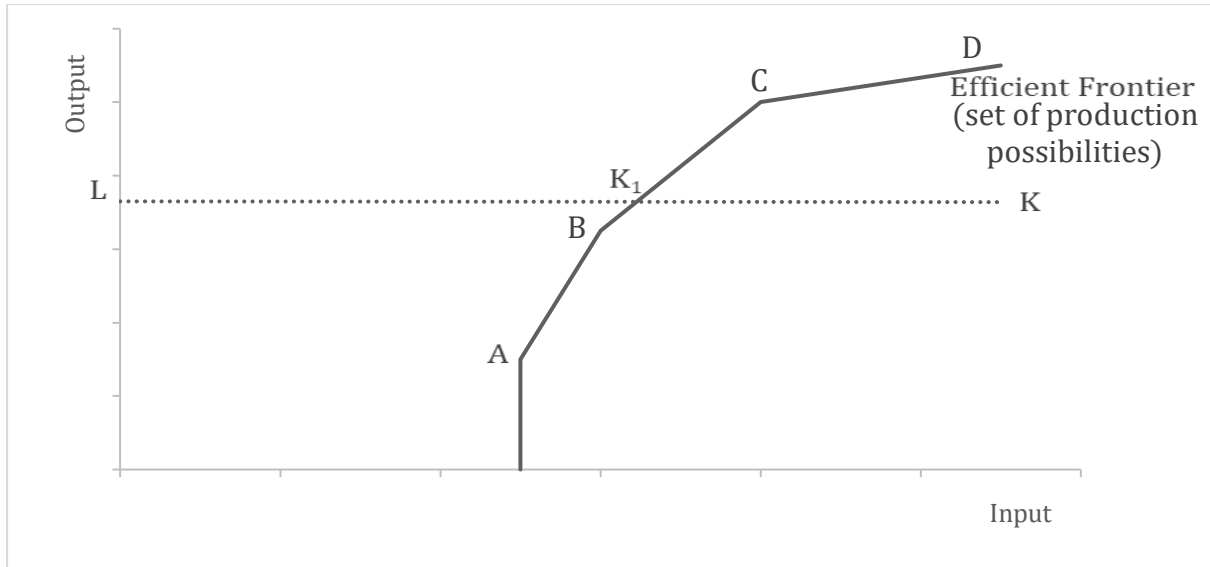


Figure 2.2. Efficiency Frontier of DEA. Source: Reenu Kumari (2019)

2.2.2. Multiple regression analysis

In the banking sector, it is a common practice to evaluate the performance of total banks, including both individual banks and the entire sector, using various financial ratios.

The use of ratios alone in evaluating the efficiency of banks carries various weaknesses and drawbacks. Ratios, which are frequently used in efficiency measurement, are insufficient when there are multiple inputs and outputs. Because, this approach is basically defined as the ratio of a single output to a single input. In cases where all inputs and outputs cannot be transformed into a common unit, the inputs and outputs subject to the efficiency measurement process have to be evaluated separately. This often leads to results that are impossible to interpret. Ratios alone do not make much sense. The evaluation of the rates together does not change the situation. If the number of inputs and outputs increases, the analysis becomes even more ineffective. Because, there are xy ratios to be examined in an analysis that has x inputs and y outputs.

Multiple regression analysis is used to overcome some of the weaknesses of ratio analysis. By means of multiple regression analysis, the relationship between the output and inputs of an organization is tried to be defined parametrically. Depending on the defined function, the output level of a certain decision-unit is predicted. Thus, decision-units with output levels above the predicted level are considered efficient, while others are classified as inefficient. The

weaknesses of this approach can be summarized in three groups. First, multiple regression requires that all outputs be reduced to a single value over a common unit, since it takes into account only one output. This is not possible when the units of the outputs are different. Secondly, regression analysis refers to the average value as the efficiency criterion, instead of finding the efficiency of the others as reference by the most efficient unit in efficiency measurement. Thus, the units found effectively as a result of the analysis are in fact only units with higher than average efficiency. Finally, regression analysis tries to determine the production function parametrically. However, different decision-units can produce with different combinations of inputs using different technologies. In other words, the assumption that the production function is defined in a single way underlying the regression analysis does not fit the nature of the decision-units subject to the efficiency analysis. In the light of all these explanations, it is concluded that regression analysis is not a suitable analysis method for efficiency measurement.

According to the DEA technique, the relative efficiency of the decision-unit is defined as the ratio of total weighted outputs to total weighted inputs. In this context, the question is how should weights be given to inputs and outputs with different units. This is the essence of DEA analysis. DEA allows flexibility in weighing inputs and outputs to each decision-unit. Thus, the fact that different decision-units may have different production functions is taken into account. Decision-units have freedom in determining weights and there are many sets of weights to choose from. But in fact, all units have the same set of weights they choose. DEA assumes that each decision-unit will choose input and output weights to maximize its efficiency score. Because different decision-units create different combinations of inputs to generate different outputs, it can be expected that weights will be chosen to reflect this diversity. Generally, decision-units will give the highest weight to the inputs they use least and the output they produce the most. The point to note here is that weights are not related to price, but are decision variables that will maximize the efficiency of the decision-unit.

The results of DEA analysis contain extremely important information in terms of management. DEA analysis measures the efficiency of each decision-unit in the set examined, relative to the others. Thus, decision-units with low efficiency are determined and data on how much their efficiency can increase is obtained. Managers can focus its attention on the least efficient units. If a decision-unit is not efficient, DEA analysis suggests the strategies required to increase the efficiency of this unit by referencing effective decision-units. In the light of this information,

the management can evaluate which inputs the ineffective decision-unit uses more than necessary, how insufficient it is producing in terms of which outputs, and what it should do to be efficient.

2.2.3. Mathematical approach to DEA

Production is the process of converting inputs into outputs. The effectiveness of this process depends on obtaining the maximum output using a certain input combination within the framework of current technology and technological change, or producing a certain output combination using the least input.

The inputs used in the production process are shown with the m dimensional X vector and the produced outputs with the s dimensional Y vector. In this context, the production technology can be defined by S as the set of all possible X^t inputs and all corresponding possible Y^t outputs. Thus, the technology S is the set of all possible input-output combinations for the period t or production unit t . Combinations not in the S set are input-output combinations that are not possible. Some elements in the set S (input-output combinations, $S^t \in S$) are less wasteful than others and are more efficient in this context. For S^t , if it is not possible to increase some of the output by keeping the inputs constant, there is no waste in the production process for this element. The lack of extravagance is expressed by the concept of "technical efficiency". In other words, technical efficiency is the success of producing the maximum possible output by using the input combination in the most appropriate way.

In this context the production function (production frontier or production frontier function) is the set of all combinations of production that are technically efficient. If the production frontier is defined as closed $F(X^t, Y^t) = 0$, $F(X^t, Y^t) < 0$ represents technically inefficient production combinations, while $F(X^t, Y^t) > 0$ defines combinations that cannot be produced using technology S . This definition of the activity was made by Koopmans (Koopmans, T. C. 1957).

In the framework of the notation used above, the technical change occurs as a result of the transformation of $S = \{(X^t, Y^t) : F(X^t, Y^t) \leq 0\}$ (production function $y = f(x)$) into $H = \{(X^t, Y^t) : G(X^t, Y^t) \leq 0\}$ (production function $y = g(x)$). Clearly, for change to be in the direction of technical progress, it must be $S \subseteq H$.

Even though efficiency and productivity (or effectiveness) are sometimes used interchangeably, they are very different in meaning they carry. Productivity is expressed as the ratio of total output to total input, and is more limited than the efficiency described above (Sudit, E.F. 1995, pp.435-453).

If cost and profit factors are also taken into account, the examination of price efficiency in addition to technical efficiency was carried out by Farrell (Farrell, M. J. 1957, pp.253-281).

In summary, success in producing the maximum possible output by using the available input combination in the most appropriate way is defined as "technical efficiency", success in choosing the most suitable input combination by considering input and output prices "price efficiency" and success in producing at the appropriate scale as "scale efficiency". All of these components together determine the "economic efficiency" (Farrell, M. J. and M. Fieldhouse 1962, pp.252-267). Technical efficiency and scale efficiency are collectively referred to as "total efficiency" or "DEA efficiency" (Banker, R.D., A. Charnes and W.W. Cooper, 1984, pp.1078-1092).

The measurement approach described above is based on the simplest case, single-input single-output. Even in this case, it is far from practical to define the production frontier based on observations and to measure the efficiency of all observations. The m -input s -output case is extremely complex compared to the single-input single-output case, and brings new problems such as different units of input-output factors. The basic technique to be used for the solution of these problems is mathematical programming. Farrell et al. (1994) examined the technical details of using mathematical programming in analysing production techniques and measuring efficiency.

Some of the first and most important contributions that enabled the use of the mathematical programming approach were made by Farrell (Farrell, M. J. and M. Fieldhouse 1962, pp.252-267). As stated before, Farrell stated that the efficiency of a firm has two basic components: technical-scale efficiency and price efficiency, and defined their combination as economic efficiency. Beyond that, he laid the foundation for the use of mathematical programming in efficiency measurement with his new ideas that measure efficiency on the input-input space and with radial distances from the "effective frontier" of observations. Farrell's approach was developed and applied by researchers such as Seitz (1970,1971) and Todd (1971).

Finding the effective frontier based on the observations for m -input s -output and calculating the radial distances of the inactive points within the effective frontier from the center are solved

by Charnes et al. (Charnes A., W.W. Cooper, and E. Rhodes, 1978,1979), based on mathematical programming. Thanks to the Data Envelopment Analysis (DEA) of Charnes et al., it has become possible to measure the relative performance of decision units within the framework of Farrell's approach in cases where inputs and outputs measured with multiple and different scales or have different measurement units make it difficult to compare efficiency between decision units. Since 1978, when the DEA was put forward by Charnes et al. Seiford's comprehensive bibliographic search (Seiford, L.M., 1996, pp.99-137) is important in showing where DEA is today.

Boles (Boles, J.N., 1966, pp.137-142) and Afriat (Afriat, S.N., 1972, pp.568-598) had mathematical programming suggestions as an extension of Farrell's important work from 1957, however, these studies did not receive much attention. With the study published by Charnes et al. In 1978, which called the approach DEA, this field started to draw intense attention.

2.2.3.1 CCR model

The fractional programming model established by Charnes et al. (1979) based on Farrell's definition and its colinear programming model (Charnes-Cooper-Rhodes Model, CCR Model) are given below. Following these models, a dual model containing some important managerial information was established.

Let there be n decision-units in the problem to be analysed, each with m inputs and s outputs. The parameter $X_{ij} > 0$ indicates the amount of input i used by the j decision-unit. Likewise, the parameter $Y_{rj} > 0$ indicates the amount of output r produced by the j decision-unit. The variables for this decision problem are the weights that k decision-units will give for the i input and r output. These weights are shown as v_{ik} and u_{rk} , respectively. At this stage, the problem can be expressed as the formulation of n fractional linear programming models for n decision-units. The objective function of the fractional linear programming model is the maximization of the ratio of total weighted outputs to total weighted inputs for k decision-units, from the definition of efficiency:

$$\max h_k = \frac{\sum_{r=1}^s u_{rk} Y_{rk}}{\sum_{i=1}^m v_{ik} X_{ik}} . \quad 2.13$$

The decision-unit k weights should be chosen in such a way that their efficiency does not exceed 1.0 when other decision-units also use these selected weights. Otherwise, the decision-unit k catches 1.0 as the efficiency value, while some other decision-units are effective over 1.0. This constraint can be expressed as:

$$\frac{\sum_{r=1}^s u_{rk} Y_{rj}}{\sum_{i=1}^m v_{ik} X_{ij}} \leq 1 \quad ; \quad j = 1, \dots, n \quad 2.14$$

It is also clear that the input and output weights to be used by the decision-unit k cannot be negative:

$$\begin{aligned} u_{rk} &\geq 0 \quad ; \quad r = 1, \dots, s \\ v_{ik} &\geq 0 \quad ; \quad i = 1, \dots, m \end{aligned} \quad 2.15$$

The fractional programming model given above can be transformed into a linear programming model and solved with the help of Simplex algorithm in this model. The model resulting from the conversion is called CCR:

CCR model

$$\max h_k = \sum_{r=1}^s u_{rk} Y_{rk} \quad 2.16$$

st

$$\sum_{r=1}^s u_{rk} Y_{rj} - \sum_{i=1}^m v_{ik} X_{ij} \leq 0 \quad ; \quad j = 1, \dots, n \quad 2.17$$

$$\sum_{i=1}^m v_{ik} X_{ik} = 1 \quad 2.18$$

$$u_{rk} \geq 0 \quad ; \quad r = 1, \dots, s$$

$$v_{ik} \geq 0 \quad ; \quad i = 1, \dots, m$$

In order to get the results of DEA analysis, the CCR model should be resolved with each decision-unit's own parameters. Note that these linear programming models are very similar to each other. The first constraint is the same for all models. Parameter change is only needed in the objective function and second constraint.

For CCR model, the dual model is set up as follows:

Dual CCR model

$$\min w_k = q_k$$

st

$$\sum_{j=1}^n \lambda_{kj} Y_{rj} \geq Y_{rk} \quad ; \quad r = 1, \dots, s \quad 2.19$$

$$-\sum_{j=1}^n \lambda_{kj} X_{ij} + q_k X_{ik} \geq 0 \quad ; \quad i = 1, \dots, m \quad 2.20$$

$$\lambda_{kj} \geq 0 \quad ; \quad j = 1, \dots, n$$

$$-\infty \leq q_k \leq +\infty \quad 2.21$$

In the dual model, the variable q and a variable λ corresponding to each decision-unit are defined. These two variables contain important managerial information. The variable q is extremely easy to interpret. Due to the duality between the two models, q_k and h_k should take equal values. Since the variable h_k gives the efficiency of the decision-unit k for the primal model, it will give the efficiency of the decision-unit k in q_k .

The interpretation for the dual variable λ is a bit more complicated. The "complementary slackness theorem" states that λ_{kj} can only have a positive value if the inequality corresponding to the decision-unit k in the primal CCR model holds as an equality. This situation indicates that the decision-unit j is effective. In other words, one of the inequalities in the model can be written as

$$\sum_{r=1}^s u_{rk} Y_{rj} - \sum_{i=1}^m v_{ik} X_{ij} \leq 0 \quad ; \quad j = 1, \dots, n \quad 2.22$$

when $\lambda_{kj} > 0$

$$\sum_{r=1}^s u_{rk} Y_{rj} - \sum_{i=1}^m v_{ik} X_{ij} = 0 \quad 2.23$$

which is the inequality that λ_{kj} corresponds to.

Therefore, in the primal model of the decision-unit k , all decision-units corresponding to all λ_{kj} dual variables with positive values are effective. The set formed by these decision-units is called the "reference set" of the decision-unit k . Generally, if k is efficient then the only decision-unit in the reference set will be itself and the value of the dual variable λ_{kk} will be equal to 1.0. The reference set for ineffective decision-units provides a prescription to the manager on what needs to be done to achieve efficiency.

The CCR model measures total efficiency under the CRS (Constant Return to Scale) assumption. In economics, returns to scale describe what happens to long-run returns as the scale of production increases when all input levels set by the firm are variable. The concept of scaled returns emerges in the context of a firm's production function. Here we can express three types of different return to scale: decreasing return to scale (DRS), increasing return to scale (IRS), and constant return to scale (CRS). If the amount of output increases less than the change in the total amount of input, there is diminishing returns to scale (DRS). On the contrary, if it is seen that the amount of output increases more than the change of the total amount of input, there is an increasing return to scale (IRS). It is shown by Banker that the direction of the return to the scale can be found using the CCR model. The total value of the dual variables in the optimal solution of the CCR model established for k decision-units shows the direction of the return to scale for k decision-units:

$$\begin{aligned} \sum_{i=1}^n \lambda_{ki} = 1 &\Rightarrow CRS \\ \sum_{i=1}^n \lambda_{ki} < 1 &\Rightarrow IRS \\ \sum_{i=1}^n \lambda_{ki} > 1 &\Rightarrow DRS \end{aligned} \quad 2.24$$

2.2.3.2 BCC model

In 1984, Banker et al. (Banker, R.D., A. Charnes and W.W. Cooper, 1984, pp.1078-1092) added the convexity constraint to the previous Charnes-Cooper-Rhodes (CCR) model under the assumption of Variable Return to Scale-VRS (Banker-Charnes-Cooper model, BCC model). Although both approaches are DEA models, their assumptions are different. While the CCR model measures total efficiency under the CRS assumption, the BCC model measures only technical efficiency by comparing units of similar scale with each other under the VRS assumption. In summary, $E_{CCR} = E_{scale} \times E_{BCC}$.

First, using the variable definitions above, the primal BCC model is given:

BCC model

$$\max h_k = \sum_{r=1}^s u_{rk} Y_{rk} - u_0 \quad 2.25$$

st

$$\sum_{r=1}^s u_{rk} Y_{rj} - u_0 - \sum_{i=1}^m v_{ik} X_{ij} \leq 0 \quad ; \quad j = 1, \dots, n \quad 2.26$$

$$\sum_{i=1}^m v_{ik} X_{ik} = 1 \quad 2.27$$

$$u_{rk} \geq 0 \quad ; \quad r = 1, \dots, s$$

$$v_{ik} \geq 0 \quad ; \quad i = 1, \dots, m$$

$$u_0 \text{ urs}$$

In the optimal solution of the BCC model, the value of u_0 variable is positive and the decision-unit is DRS, negative value is IRS and zero value indicates CRS state.

The Dual BCC model is as follows:

Dual BCC model

$$\min w_k = q_k$$

st

$$\sum_{j=1}^n \lambda_{kj} Y_{rj} \geq Y_{rk} \quad r = 1, \dots, s \quad 2.28$$

$$-\sum_{j=1}^n \lambda_{kj} X_{ij} + q_k X_{ik} \geq 0 \quad i = 1, \dots, m \quad 2.29$$

$$\sum_{j=1}^n \lambda_{kj} = 1 \quad 2.30$$

$$\lambda_{kj} \geq 0 \quad j = 1, \dots, n$$

$$-\infty \leq q_k \leq +\infty$$

However, it has been shown by Banker and Thrall (Banker, R.D. and R.M. Thrall, 1992, pp.74-84) that the findings of Banker et al. are valid only when there is one optimal solution. In the same study, in the case of more than one optimal solution, it is explained that u_0 defines the CRS, IRS and DRS states for $u_0^- \leq u_0 \leq u_0^+$, $u_0 \in R^-$ and $u_0 \in R^+$, respectively, as $u_0^- \in R^-$ and $u_0^+ \in R^+$, and how to find u_0^- lower and u_0^+ upper limits.

2.2.4. Application stages of DEA

Selection of Decision-Making Units: The first step of DEA is selecting DMUs to form the observation set to be used in efficiency measurement. The fact that DMUs have similar characteristics, that is, the observation cluster is homogeneous, is essential for successfully implementing the analysis (Gokgoz, 2009). Furthermore, he stated that the number of DMUs must be above a particular value for efficiency measurements to differ from each other (Yolalan, 1993).

Determination of inputs and outputs: DEA is a data-based efficiency measurement technique, forming the basis of step analysis. For the measurement to be made with DEA to be healthy, the handled inputs must be meaningful. When it is desired to increase the number of input-output variables, the number of DMUs will also need to be increased, so the input-output variables should be as low as possible, but they should best represent the process under consideration.

Accessibility and reliability of data: After selecting the input-output variables in DEA, it is time to reach the data of these variables. For the successful implementation of DEA, it is crucial to organize the data of inputs and outputs for all DMUs as a database and be reliable. If the

data for any DMU is unavailable or if the reliability of the data is suspected, it is necessary to remove the DMU from the analysis.

Evaluation of the efficacy result: At this stage, the effective values of the DMUs are calculated, and the effective and ineffective DMUs are determined. The reference set is created for inactive DMUs. Finally, a general evaluation is made for active and ineffective DMUs.

2.3. DETERMINATION OF INPUTS AND OUTPUTS IN THE BANKING SECTOR

One of the most problematic and disputed points in measuring efficiency in the banking sector is what the inputs and outputs are. The issue of what inputs and outputs will consist of is not yet agreed in the literature (Elyasiani E. and S. Mehdian 1990, pp. 539-551). This problem affects the technique we will choose to measure efficiency, the variables we will accept as inputs and outputs, and the results we finally get. The issue of uncertainty of inputs and outputs arises from three situations related to the nature of banking activity:

1. Banks do not produce a physical good; they mainly produce service, and measuring and calculating this service is quite problematic.
2. Banks use the large number of inputs and outputs.
3. There are difficulties in defining the basic function of banks.

These qualities of the banking system have enabled the development of two different approaches in measuring bank inputs and outputs. These are called production and intermediation approaches.

2.3.1. Production approach

The production approach handles banks, capital, labour, and other materials (branches, fixtures, etc.) as inputs, whereas deposits, loans, security portfolios, and other balance sheet items as outputs. In the production approach, banks are considered as institutions that produce outputs such as time and demand savings deposits, commercial loans, real estate acquisition, and facility loans by using resources (input) such as labour, cash, and capital. In the production approach, the number of accounts as output and the monetary values of the accounts are used

in the intermediation approach. From an input point of view, only operating costs are considered in the production approach, while the intermediation approach also includes the cost in terms of interest.

The question of which of these two approaches will be chosen is directly related to the problem the researcher seeks to solve. Thus, for example, the production approach is adopted in studies aiming to investigate the cost efficiency of banks (Ferrier, G.D. and C.A.K. Lovell, 1990, pp.229-245), while the intermediation approach is an appropriate method to be used in cases where the total cost of the banking sector and the economic competitiveness of banks are investigated.

The factors chosen as input and output in studies differ in number and type. So, naturally, researchers have to select factors and quantities in line with the purpose they pursue. It can be said that neither public capital institutions (public banks established by law) nor private capital commercial banks have contradictions in terms of their purpose functions. It is known that it is a legal obligation that state banks with the status of State Economic Enterprise should work in accordance with the principles of profitability and efficiency, just like private sector organizations. In this context, banks should increase their share in the deposit market and increase their contribution to the supply of loanable funds and ultimately make a profit required the selection of total deposit, total loan, and net profit factors as outputs of these institutions. These factors are expressed in terms of "monetary values" as in the intermediary approach, not the number of accounts as in the production approach.

2.3.2. Intermediation approach

Considering that the primary function of the banking system is to act as an intermediary between funds that are borrowed and funds that are lent, the intermediation approach sees deposits and other resources as the bank's input, and loans and other assets as the bank's output, in line with this assumption. Therefore, this approach uses the currency unit, not the number of accounts, when measuring inputs and outputs.

These two approaches are distinguished by specifying the differences between the two methods used to calculate the bank's unit cost. Accordingly, the operating expenses of the bank can be calculated by two methods. First, you divide operating expenses by either the total deposit volume or the size of assets or the number of deposit accounts.

Dividing operating expenses by deposit volume or asset size tells us how many euros we spend on operating a one-euro deposit or asset, and this figure gives us a basis for comparing different examples with each other in terms of efficiency. Furthermore, this method is suitable for the intermediation approach because, according to the intermediation approach, the function of banks is to mediate funds in the economy and transfer them to productive fields. From this perspective, since the total active loan or deposit size will show the total amount of resources mediated by the bank, the cost should be calculated according to these outputs.

On the other hand, the unit cost, which we calculate by dividing the operating expenses by the number of deposit accounts, shows us how many cents we spend to operate a single account. The cost measurement method based on the number of accounts fits with the production approach because the production approach tells us that bank accounts (whether it is a loan or deposit account) are the bank's product.

This is the difference between the two methods in our calculations if we only consider operating expenses. But when we add financing expenses (interest and foreign exchange expenses) to this, there is another important difference. Since the production approach does not consider deposits and other borrowed funds as input, it does not include the financing expenses, which are the price of these funds, in the total cost. On the other hand, since these variables are considered inputs in the intermediation approach, financing expenses are also included in the total cost. This situation results in the fact that the production approach does not consider the financing costs and, as can be easily predicted, has led to many criticisms.

CHAPTER 3

LITERATURE REVIEW ON BANKING EFFICIENCY WITH DEA

3.1 LITERATURE REVIEW ON BANKING EFFICIENCY

In this part of the thesis, the studies on data envelopment analysis in the banking sector have been examined, and the results of my study have been compared.

The literature review shows that there are many studies on measuring the efficiency of banking with DEA method. Banks are among the important actors of the financial sector. Banks are institutions that maximize their value while taking risks by providing an intermediary function between fund suppliers and demanders in the money market. The fact that the DEA method is used in the study is also crucial in determining the input and output variables to be used properly.

In the efficiency measurements, examinations are made according to different criteria, and it has been investigated whether it is effective according to input and output principles. In the light of these studies, the input and output variables that were taken as a basis for examining efficiency and productivity were decided.

In the article written by Duarte Neves et al. (2020), the value measurement of a total of 94 commercial banks in European countries was discussed. The aim of the study is to address other external factors that may affect performance and efficiency values in 94 commercial banks considered between 2011 and 2016 and to conduct a productivity analysis on this. The study, based on the five years immediately after the financial crisis, also shows how the banking structure of Europe was affected by this crisis. For the efficiency measurement, firstly, the efficiency of some in-bank factors was measured with the generalized method of moments (GMM), and then the effective banks were found through the value-based DEA technique. In the value-based DEA method, the "number of employees," "cost-to-income ratio," and "net loans to total assets" are used as an input value, while "return on average assets" and "equity to

total assets" are used as an output value. According to the results of the article, it was determined that among the years analysed, the efficiency rates of banks were higher in 2011 and 2014, although there was a general inefficiency. In 2011, 2012, and 2016, the productivity ratios of banks were higher than 0.8, and the value ratio of productive banks in Germany (3) and France (2) among these countries was higher than in other countries.

In a study on the productivity of Vietnamese banks (Stewart et al., 2016), ten years of input and output data from 1999 to 2009 were used to measure the performance of banks. A two-stage analysis was conducted to get reliable results. In the first stage, a DEA analysis was performed using the constant returns to scale (CRS) and variable returns to scale (VRS) methods. However, in the second stage, the Simar and Wilson (2007) procedure was applied to DEA analysis with a truncated bootstrapped regression. As a result of the research, it has been determined that larger banks are more efficient than smaller and medium-sized banks, and it has been revealed that smaller banks have the least productivity in the country. It is also among the results that private commercial banks are more efficient than state-owned commercial banks.

The most important function of the banking sector is to act as an intermediary within the financial systems. Banks act as intermediaries by transferring the deposits collected from savers to those in need. It offers these savings to the needy in line with their requirements (housing loans, consumer loans, business loans, etc.). Customers can also be given a share of the profit it makes for customers who want to prevent the loss of money while protecting their customers' savings. The globalizing economy increases the competition level of banks.

For this reason, banks should increase their efficiency levels and make improvements on the correct input-output units. There are various approaches in the measurement of the efficiency with DEA in the banking sector. The main problem here is that deposits are used as input or output. The input-output units vary according to the approach used. These approaches are as follows:

Production approach: In this approach, banks are like systems that produce. They convert the number of employees, cash, and similar capital into accounts and loans. Deposits are calculated as the output according to the production approach. In studies conducted in this area (Berger and Humphrey, 1978), it has been revealed that the production approach is more suitable for the analysis of small branches of large banks.

Intermediation approach: In this approach, banks operate as major intermediary institutions. Banks mediate the conversion of deposits collected from savers into loans and other assets and therefore account for deposits as inputs.

Value-added approach: Banks want to maximize their profits and minimize their costs. For this reason, in this approach, interests given to depositors are considered inputs, while interests and non-interest incomes from loans are considered outputs.

Holod et al. (2011) dealt with this issue in their study. According to Holod et al. (2011), one of the biggest problems in the productivity calculation of banks in today's production process is that it is not decided to calculate deposits as input or output. The study has been prepared based entirely on researching how the deposit is calculated. In this study, the author treats deposits as an intermediate product in the data envelopment analysis, thus revealing the dual role of deposits. To do this, a two-stage DEA model was used in the study. In the first level, the deposit was analysed as an output, and in the second level, the analysis was made using the same outputs as input. As can be seen in figure 3.1, the gradual analysis consists of three steps. In the first step, the input is x_k ; in the second step, we use the intermediate product y_k , and in the last step, the output z_k is used.

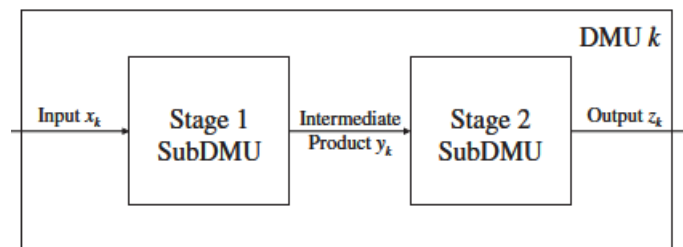


Figure 3.1 Two-stage DEA with one input, one intermediate product, and one output. Source: Holod et al. (2011)

As a result, deposits can be thought of as inputs or outputs depending on the bank's production process. Thus, the efficiency of the number of deposits on overall bank productivity depends on the degrees of efficiency on both sides.

Efficiency is a general concept that determines qualitatively and quantitatively what is owned as a result of a targeted and planned activity, defined as the level of fulfilment of a job, goods, or services or the attitude of the person who does the job according to the specified conditions. There are different combinations for these inputs and outputs in systems that create similar

outputs using similar inputs. These combinations contain information about what inputs will be used and what outputs will be produced at what proportions for decision-making units (DMU). Non-parametric methods have been used in efficiency measurement models for systems with a large number of inputs and outputs.

In systems with multiple inputs and outputs, DEA can be measured without a predetermined production function as in parametric methods. In this respect, DEA studies have become an essential tool in performance evaluation in the banking sector.

In this field, an article written by Christopoulos et al. (2020) is important. The aim of the study is to measure the efficiency of banks in PIIGS (Portugal, Italy, Ireland, Greece, and Spain) countries of Europe in the period between 2009-2015 after the financial crisis, using the data envelopment analysis method. As a measurement method, more than one instrument was used, firstly the analysis was made with the output-oriented CCR model, and then the efficiency level was evaluated with the Malmquist TPF Index. The reason for making more than one measurement in the research is that more than one factor affects the bank's efficiency, so it is better to get healthy results by making multi-directional analyses. In the CCR model, "operating cost," "total assets," and "number of employees" are used as input, and "net income" is used as an output. As can be seen, only one output was chosen in the analysis.

As a result, statistical findings show that there is inefficiency in many analysed banks. As a result of this DEA analysis, it was seen that PIIGS countries reacted differently in the period after the crisis. According to the analysis of Portuguese and Italian banks, it has been determined that they are more durable and efficient than the banks of other countries. At the same time, the negative productivity of many banks during this period indicates that the banks of PIIGS countries did not fully recover from the impact of the crisis after the financial crisis.

Día et al. (2020), in their studies, considered six major banks of Canada and evaluated the performance of banks between the years 2000 and 2017. The purpose of the assessment is also to evaluate the efficiency of banks before and after the financial crisis of 2007 and the impact of increasing competition on banks with developing technologies. Using a three-stage network DEA technique, it was determined that the 2007 crisis caused poor performance in Canadian banks. The bootstrap technique has been used with this three-stage (production stage, intermediation stage, and revenue generation stage) network DEA. Accordingly, the efficiency ratios of individual banks were not the same, showing different results at each stage. According

to the results, after 2011, Canadian banks tended to reduce operating costs and non-operating costs against the financial crisis.

The most used model in data envelopment analysis is the CCR model, then the BCC model. Optionally, one of the two models can be used for analysis, but some researchers can perform comparative analysis using the two models in the same study. One of these is the research conducted by Cotrim Henriques et al. (2018) to evaluate the efficiency of Brazilian banks. The article aims to analyse the efficiency and performance of 37 Brazilian banks between 2012 and 2016 using input-oriented CCR and BCC models. According to the analysis results, the efficiency rate of Brazilian banks was 51.4% according to the Charnes, Cooper, and Rhodes (CCR) model, while this figure was 69.8% according to the Banker, Charnes, and Cooper (BCC) model. Big banks performed better in terms of the pure technical efficiency model. According to the results, while large banks exhibited decreasing returns to scale, smaller banks exhibited increased returns to scale.

In Drake et al. (2003), the productivity of Japanese banks was evaluated using an input-oriented non-parametric DEA frontier approach. "General and administrative expenses," "fixed assets," "retail and whole sale deposits" were used as inputs, and "total loans and bills discounted," "liquid assets and other investments in securities," "other income" were used as output. The results show that the efficiency rates of big city banks in Japan are generally higher than the minimum efficiency rate, but this is not to say for smaller banks. It was also stated that in the Japanese economy, especially in small banks, the control of non-performing loans (NPL) should be increased.

In many of the articles mentioned above, the productivity rate of large banks has been higher than that of smaller banks. The reason for this may be that big banks are more advantageous in financial terms. In the article written by Kilian Huber (2017), it was stated that big banks were not big by chance; on the contrary, they were grown because they were administratively well managed and efficient.

In terms of showing the effect of financial freedom on banks' productivity, significant findings were found in the study by Chortareas et al. (2013) evaluating the efficiency rates of commercial banks in 27 countries in the European Union. As a result of the study, it is stated that the high financial freedom of the economies is of great importance in terms of increasing the cost advantage and general efficiency of banks. In the article written by Chortareas et al.

(2013), input-oriented DEA analysis was performed with the variable returns to scale (VRS) method. According to the results of the analysis, it is seen that the effect of financial freedom on the economic efficiency of banks is felt more in large countries that develop more freely fiscal policies and are less economically dependent.

Parametric methods usually have a set of observations, and within this set of observations, the best performance is assumed to be on the frontier of the regression line. The efficiency of the observations depends on their not deviating from the regression line. In this method, it is assumed that there will always be a random error. Observations with zero error are fully efficient observations.

Casu et al. (2002) used the stochastic cost frontier analysis (SFA) and a CCR model in data envelopment analysis in their study to evaluate the efficiency rate of the big bank conglomerates and branches of these same banks in Italy. "Labour cost," "deposits," and "physical capital" were used as the input value, and "total loans" and "other earning assets" were used as output. The results of the study conducted by Casu et al. (2002) show that bank groups are not entirely successful in increasing economies of scale and reducing X-inefficiency. In addition, it is stated that the size of the bank is not the main factor in increasing cost efficiency in Italian banking. Furthermore, there is evidence that large bank holdings have more financial freedom and may gain greater coverage benefits than smaller branches of the same banks.

In the article written by Hoang Nguyen et al. (2020), a comprehensive comparison of DEA and SFA models has been made. In the article, an analysis was made using the same data on the cost efficiency of Vietnam banks using DEA and SFA models. For making an analysis, "deposits," "labour cost," and "physical capital" were used as inputs, "loans," "other earning assets," and "off-balance sheets" as output values. This inconsistency in the measurements of two different models shows that the model to be used while working on efficiency and the selection of the data and the careful analysis are very important in obtaining beneficial results.

In table 3.1 below, there is all literature used for writing this chapter.

Table 3.1 Literatures on banking efficiency

Study	Objective	Country	Method used	Inputs	Outputs	Results
Cristopoulos et al. (2020)	to assess the relative banking efficiency of the Eurozone's soft underbelly (i.e., the so called PIIGS countries: Portugal, Ireland, Italy, Greece and Spain) in the period after the outburst of the financial crisis.	PIIGS countries	CCR (output-oriented) Malmquist Productivity Index (MPI) truncated regression	Operating Cost, Total Assets, Number of Employees	Net Revenues after provisions	Findings show statistical evidence of a high degree of inefficiency in most of the examined banks. According to the results of DEA, the reaction of the banking sector in the aftermath of the global financial crisis differs between the PIIGS members. In effect, Portuguese and Italian banks seem to perform better on average in the period under investigation.
Dia et al. (2020)	to evaluate the performance of the six big Canadian banks for the period 2000–2017, amid the 2007 financial crisis and the increasing competition level due to new technologies.	Canada	Three stage network DEA the production stage, intermediation stage, and revenue generation stage.			Results indicate that the 2007 financial crisis resulted in lower efficiencies in the performance of Canadian banks. This decline was not substantial for the production and investment stages when the revenue generation stage received the greatest hit.
Duarte Neves et al. (2020)	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.	Eurozone countries	value-based DEA, generalized method of moments (GMM) method.	Number of employees, Cost-to-Income Ratio, Net Loans to Total Assets	Return on Average Assets, Equity to Total Assets	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 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).
Hoang Nguyen et al. (2020)	to enrich previous findings for an emerging banking industry such as Vietnam, reporting the difference between the parametric and nonparametric methods when	Vietnam	Input oriented DEA, and SFA	Deposits, Labour cost and Physical capital	Loans, Other earning assets and Off-balance sheet	The results show that the cost efficiency obtained under the SFA models is more consistent than under the DEA models. However, the DEA-based efficiency scores are more similar in ranking order and stability over time.

	measuring cost efficiency.					
Ferriera (2019)	to contribute to the analysis of the bank efficiency in the European Union in the aftermath of the recent crisis, using DEA and considering a sample of 485 banks from all current EU member-states between 2011 and 2017.	European Union	DEA, Malmquist TFP index Panel data estimates.	Interest expenses, non-interest expenses, and Equity	Loans, Other earning assets and non-earning assets	The results obtained confirm the existence of bank inefficiency, and that this inefficiency is mostly due to inefficient managerial performance and bad combinations of the considered bank inputs and outputs.
Cotrim Henriques et al. (2018)	to evaluate bank efficiency in the period from 2012 to 2016 by applying Data Envelopment Analysis (DEA) in a dataset of 37 Brazilian banks provided by the Brazilian Central Bank.	Brazil	Input oriented CCR and BCC	Fixed assets, Total deposits and Personnel expenses	Total loans	Brazilian banks presented an average efficiency of 51.4% for the (CCR) model and 69.8% for the (BCC) model. The largest banks have performed well in regards to Pure Technical Efficiency (PTE), but failure to operate at the optimal scale level has impaired Technical efficiency (TE). These banks, in the majority, presented decreasing returns to scale, while the smaller banks had increasing returns to scale.
Stewart et al. (2016)	To analyse the efficiency of the Vietnamese banking system from 1999 to 2009 by identifying the determining variables for bank efficiency.	Vietnam banking system	Two stages: CCR, BCC and bootstrap.	Number of employees, deposits from other banks and client deposits.	Loans from customers, other loans and securities.	The largest banks were more efficient than the medium and small banks, with small banks being the most inefficient. As far as global efficiency is concerned, private banks were more efficient than state-owned banks.
San-Jose et al. (2014)	To contribute to quantify the magnitude of efficiency, but not only the economic one, but also social and overall efficiency from 2000 to 2011. The case of Spain – compared to other banking systems	Spain	DEA with value-added approach.	Equity, Total assets, Deposits	Profit, Loss, Risk	The results indicate that Spanish savings banks are not less efficient globally than banks and are more efficient socially. Moreover, our results – with potentially important implications – encourage the participation of stakeholders in banking systems and underline the importance of attaining long-term efficiency gains to support financial stability objectives.

Chortareas et al. (2013)	To investigate the dynamics between the financial freedom counterparts of the economic freedom index drawn from the Heritage Foundation database and bank efficiency levels. This paper relies on a large sample of commercial banks operating in the 27 European Union member states over the 2000s	European Union	Input oriented DEA model VRS	Personnel expenses, Total fixed assets, Interest expenses	Total loans, Total other earning assets	Results suggest that the higher the degree of an economy's financial freedom, the higher the benefits for banks in terms of cost advantages and overall efficiency. Our results also show that the effects of financial freedom on bank efficiency tends to be more pronounced in countries with freer political systems in which governments formulate and implement sound policies and higher quality governance.
Chortareas et al. (2012)	To investigate the dynamics between key regulatory and supervisory policies and various aspects of commercial bank efficiency and performance for a sample of 22 EU countries over 2000–2008.	European Union	Input oriented DEA Model VRS, truncated regression model	Personnel expenses, Total fixed assets, Deposits and short-term funding	Total loans, Total other earning assets, Fee-based income	Results show that strengthening capital restrictions and official supervisory powers can improve the efficient operations of banks. Evidence also indicates that interventionist supervisory and regulatory policies such as private sector monitoring and restricting bank activities can result in higher bank inefficiency levels.
Holod et al. (2011)	To propose an alternative Data Envelopment Analysis (DEA) bank efficiency model that treats deposits as an intermediate product, thus emphasizing the dual role of deposits in the bank production process.	Deposit dilemma- is it input or output				Recognize that deposits may be considered as either an output or an input, depending on the stage of a bank's production process. As a result, the effect of the amounts of deposits on the overall bank efficiency depends on the efficiency at both stages.
Drake et al. (2006)	To assess the relative technical efficiency of institutions operating in a market that has been significantly affected by environmental and market factors in	Hong Kong	Slack Based DEA Model, Tobit regression	Employee expenses, non-interest expenses and Loan loss provisions.	Net interest income, Net commission income and Total other income.	The results indicate: high levels of technical inefficiency for many institutions; considerable variations in efficiency levels and trends across size groups and banking sectors; and also, differential impacts of environmental factors on different size groups and financial sectors.

	recent years, the Hong Kong banking system.					
Drake et al. (2003)	To analyse the technical and scale efficiency in Japanese banking using a recent cross-section sample. Efficiency analysis is conducted across individual banks, bank types and bank size groups.	Japan	Input-oriented DEA	General and administrative expenses, Fixed assets, Retail and whole sale deposits.	Total loans and bills discounted, Liquid assets and other investments in securities, Other income;	Japan is questioned as the larger (City) banks are generally found to be operating above the minimum efficient scale and to have limited opportunity to gain from eliminating X-inefficiencies. The opposite result is found for the smaller banks. Finally, the results suggest that controlling for the exogenous impact of problem loans is important in Japanese banking, especially for the smaller regional banks.
Casu et al. (2002)	To investigate the cost efficiency of Italian banking groups by evaluating the cost characteristics of bank parent companies and bank subsidiaries that form part of these groups.	Italia	stochastic cost frontier (SFA) approach and CCR model	Labour Cost, Deposits and Physical Capital	Total Loans, Other Earning Assets	The results suggest that bank groups have been unable to exploit fully scale economies and potential X-inefficiency reductions. Furthermore, bank size seems not to be the main determinant of cost efficiency in Italian banking. Nevertheless, there is sufficient evidence to conclude that bank conglomerates can gain relatively greater scope benefits compared with the single banks forming the group.

CHAPTER 4

RESULTS OF THE DEA ANALYSIS ON SELECTED EUROPEAN BANKS

4.1 INTRODUCTION

In this part of our thesis, we will share the results of our analysis and share our interpretation, that is, our thoughts, in accordance with these results. In this study, we evaluated the efficiency of the leading banks of 24 countries, which are members of the enlarged European Union, and thus the leading top 102 banks of Europe with Data Envelopment Analysis. Although there are more than 24 countries in the European Union, some countries' banks were not included in the assessment because the amount of their total assets were small compared to other European leading countries. In some countries with larger economies, more banks were included in the assessment than others, while only one or two banks of few countries were included in this efficiency analysis. While selecting banks, their total assets and other values (number of employees, net annual income, total loan amount, etc.) were also considered.

The total number of decision-making units in the assessment is 102, and the year of collected data for each bank is 2019, i.e., 102 different bank's data were analysed for a single year. Due to the current emergency called "Covid-19", there are significant differences in the current status of many banks, but during the collection of data, although there are updated data in the reports prepared for various periods of 2020 in some banks, many banks do not have data for this period. For this reason, the most up-to-date 2019 year for which all data are available for selected banks is taken as a basis. The chosen banks in this study are generally commercial banks; however, there are a few different banks. As a definition, commercial banks are banking whose primary function is to collect the public's savings as deposits and extend short-term loans to their customers. In addition, data were used in other banks such as investment banks; within the decision-making units, we use together with commercial banks.

For the collection of the necessary quantitative data, we relied on the "Orbis" database made available by Bureau Van Dijk, which contains more than 400 million companies as a data source, contains financial and administrative information of banks and various companies worldwide, and is the most important information supplier in the world, to ensure the data of the analysis made using data envelopment analysis, which is widely used in the literature for the evaluation of efficiency. Of course, although it is not often repeated, some banks have data deficiencies, and then the data of the annual reports published by companies were used.

4.2 INPUTS AND OUTPUTS USED AND SELECTED MODELS

The most important thing to make a reliable and accurate analysis assessment is choosing the banks' inputs and outputs correctly. When selecting these data for analysis, we used the article of Henriques et al. (2018), mentioning the overall efficiency analysis of Brazilian banks. According to this study, three inputs and one output were used while analysing the efficiency of banks, and these are as follows: inputs- fixed assets, total deposits, personnel expenses, output-total loans. Although we used these values in our study, we added one more output value. Thus, the inputs used in our study were determined as fixed assets, total deposits, number of employees, outputs-total loans, other-earning assets.

To summarize the inputs and outputs briefly, fixed assets record the financial value of the assets owned by the bank. This shows that money and an individual or business are valuable. There are two important asset classes. These are tangible fixed assets and intangible assets. It includes various subclasses, including tangible fixed assets and current assets. Having more assets of the bank may mean that it works well and more efficiently, but fixed assets are used as inputs in efficiency analysis, so since the short description of the efficient bank is to obtain the maximum output with the least input, it is necessary to minimize the inputs as much as possible.

Deposits are money deposited to banks and similar credit institutions to be withdrawn at any time or the end of a certain maturity or notice period. There are various approaches to whether deposits are input or output, and we have chosen the most used approach and used deposits as input. The deposits collected within the bank are then used to increase the bank's efficiency

and other financial issues. Even though personnel expenses reflect the bank's expenses well, the number of employees in the company is also a good indicator to have an idea about the size and efficiency of the company. Therefore, considering the number of employees as input is an important value in the analysis measurement of banks.

Loans is a banking service that includes various interest rates for those in need who apply for a loan, with payment methods arranged within a certain period. Since loans are one of the most important sources of income for banks, they give satisfactory answers about the actual bank's size, possibilities, and capabilities in the efficiency assessment. On the other hand, it is known that banks can earn income in different ways besides loans. It is possible to show "loans and advances to banks," derivatives, "and" other securities "as examples. As 'other earning assets' constitute income sources of banks like loans, it will be a factor for effective analysis as an output value.

In this study, data envelopment analysis was conducted to perform the analysis, as I mentioned in chapter 2. Although there are many different models for successfully applying data envelopment analysis, the two most used in today's literature are; BCC and CCR models. Although we used both models in the analysis, non-parametric tests were generally performed according to the BCC model results. For this reason, let's briefly recall this model again, although we mentioned it in chapter 2.2.3.

As we mentioned before in our sample, we have $n = 102$ DMUs (*decision making units*) where each $DMU_k, k = 1, 2, \dots, 102$, produced the same $r = 2$ outputs in different amounts, $u_{rk} (r = 1, 2)$, using the same $i = 3$ inputs, $v_{ik} (i = 1, 2, 3)$ also in different amounts. The parameter $X_{ij} > 0$ indicates the amount of input $i = 3$ used by the j decision unit, and the parameter $Y_{rj} > 0$ indicates the amount of output $r = 2$ produced by the j decision unit. The variables for this decision problem are the weights that k decision units will give for the i input and r output. With all these definitions we can write the maximization of the ratio of total weighted outputs to total weighted inputs for $k (k=1, 2, \dots, 102)$ decision-units as follows:

$$\max h_k = \frac{\sum_{r=1}^2 u_{rk} Y_{rk}}{\sum_{i=1}^3 v_{ik} X_{ik}} \quad (4.1)$$

Here h_k is the efficiency of the decision-unit k for the model. The decision-unit $k (k=1, 2, \dots, 102)$ weights cannot exceed 1.0 when other decision-units also use these selected weights.

$$\frac{\sum_{r=1}^2 u_{rk} Y_{rj}}{\sum_{i=1}^3 v_{ik} X_{ij}} \leq 1 ; \quad j = 1, 2, \dots, 102 \quad (4.2)$$

The input and output weights cannot be negative:

$$u_{rk} \geq 0 \quad ; \quad r = 1, 2, \dots, 102 \quad (4.3)$$

$$v_{ik} \geq 0 \quad ; \quad i = 1, 2, \dots, 102 \quad (4.4)$$

Before moving on to the analysis results, I want to share the basic statistics about inputs and outputs. Table 4.1 contains general statistical data of three input and two output variables. In this table, mean, median, 1st quantile, and 3rd quantile variables are shown, together with the minimum and maximum value of each input and output values from the collected data.

	Fixed assets	Number of employees	Deposits	Total loans	Other-earning assets
Min.	13,170	469	2,682,264	3,125,384	460,567
1st Qu.	349,738	4,543	40,480,000	32,950,000	12,450,000
Median	712,964	10,222	79,705,204	71,785,995	29,668,215
Mean	2,789,813	28,375	217,122,187	171,866,257	146,004,007
3rd Qu.	2,214,205	32,978	250,400,000	235,700,000	145,800,000
Max.	44,210,838	235,000	1,763,392,000	1,053,100,861	1,371,884,000

Table 4.1 Basic statistics of input and output variables

When we look in general, we know that there are significant differences, such as the gap between the minimum and maximum of all input and output values, which means that the DMU selection covers different banks operating in the European economy. This allows us to make a healthy efficiency analysis for the whole of Europe.

Countries	DMU	Inputs			Outputs	
		Fixed assets	Number of employees	Deposits & short-term funding	Total Loans	Other-earning assets
Austria	Erste Group Bank	2,953,696	47,284	209,541,865	178,465,049	77,407,395
	Raiffeisen Bank International AG	1,716,321	46,873	134,238,382	102,458,810	37,819,791
	BAWAK P.S.K.	444,866	4,346	39,442,569	34,607,456	13,743,674
	Unicredit Bank Austria AG	1,163,842	5,301	80,838,730	71,085,373	32,656,110
	KBC Group NV	4,529,224	37,629	231,467,553	175,043,672	133,431,818
Belgium	Belfius Bank SA/NV	711,358	6,525	106,967,182	105,325,560	78,251,635
	Argenta	29,203	1,030	40,566,556	37,122,588	15,340,624
	Bank of Cyprus Public Company	323,600	3,672	19,539,366	12,044,915	3,255,413
Cyprus	Hellenic Bank Public Company	204,012	3,015	16,598,956	6,716,974	5,344,650
	Ceska Sporitelna a.s.	554,485	9,872	56,821,893	31,979,534	12,169,798
Czech Republic	Komercni Banka	465,408	8,351	40,453,076	28,613,192	17,091,243
	Danske Bank A/S	2,109,678	22,006	218,592,549	273,668,718	267,653,649
Denmark	Nykredit A/S	133,465	3,515	55,612,427	202,737,009	29,584,925
	Jyske Bank	678,560	3,614	25,989,155	65,854,342	27,040,848
	Sydbank	181,249	2,030	14,544,706	9,070,537	11,628,994
	Spar Nord Bank	114,591	1,549	8,589,254	6,464,597	7,000,704
	Nordea Bank Abp	2,249,047	29,000	275,586,835	362,566,069	187,680,797
Finland	OP Financial Group	588,662	12,226	90,587,594	102,749,521	44,798,939
	AlandsBanken	35,949	469	4,019,565	4,617,206	996,007
	Bnb Paribas	35,594,924	198,816	1,271,761,655	905,389,508	1,168,268,444
France	Credit Agricole	6,288,792	73,037	972,430,641	443,840,678	1,364,637,615
	Societe generale	31,980,947	149,022	706,093,880	508,965,291	774,011,265
	Groupe BPCE	2,577,079	98,790	822,218,600	194,548,140	561,602,191

	Credit Mutuel Group	4,942,959	82,794	544,438,888	549,463,856	369,307,591
	La Banque Postale SA	889,733	5,321	249,090,326	119,937,539	154,591,054
	Banque Palatine	56,507	1,283	14,548,140	10,913,493	5,083,609
	Credit du Nord	509,349	7,494	73,460,127	52,353,354	18,551,039
Germany	Deutsche Bank AG	5,538,361	87,597	736,848,075	479,490,649	752,916,063
	DZ Bank AG	1,566,019	30,825	306,280,366	206,717,930	356,044,733
	Commerzbank AG	3,916,172	48,512	347,678,774	277,314,624	175,262,735
	KFW Bankgruppe	1,146,991	6,705	21,968,084	143,781,700	390,047,799
	HypoVereinsbank	2,816,363	12,194	217,789,036	136,732,366	168,990,793
	Landesbank Baden-Wurtemberg	914,447	10,005	167,096,741	116,510,046	145,677,999
	Bayerische Landesbank	611,130	8,316	114,520,504	161,807,775	78,985,120
	Landesbank Hessen-Thüringen	733,580	6,283	122,086,603	132,379,192	80,508,451
Greece	Piraeus Bank SA	1,172,829	11,615	56,896,832	44,050,755	7,596,430
	National Bank of Greece	1,926,631	8,600	54,032,163	32,827,991	19,557,268
	Alpha Bank	957,510	10,530	56,872,755	44,111,721	15,214,906
Hungary	OTP Bank	1,267,000	39,971	54,233,000	11,247,435	21,282,170
	K&H Bank	163,218	3,499	9,387,657	5,210,474	5,282,442
	Erste Bank	101,503	3,174	7,648,090	5,294,537	3,770,862
	CIB Bank	81,353	2,145	5,771,887	3,471,975	3,018,012
Ireland	Bank of Ireland Group plc (BOI)	1,133,510	10,440	95,978,790	89,295,684	43,435,132
	Allied Irish Bank	902,090	9,520	81,592,531	68,318,439	22,812,881

	Ulster Bank Ireland	103,353	2,237	26,614,466	23,998,068	9,223,113
Italy	Intesa Sanpaolo	9,973,544	84,774	488,122,853	470,466,378	388,169,475
	UniCredit	12,466,368	96,145	683,632,624	589,553,503	311,482,831
	CDP Group	44,210,838	33,695	386,282,830	349,962,778	80,564,472
	Banco BPM	4,071,552	21,013	137,754,938	137,405,956	36,018,020
	Banca Monte dei Paschi di Siena	3,043,409	21,420	108,638,446	99,965,884	39,044,416
	Banca Nazionale del Lavoro	1,844,705	12,399	81,085,346	72,486,618	13,275,259
	BPER Banca	1,537,593	12,479	72,235,030	67,937,457	14,661,206
	Mediobanca	325,296	4,932	43,083,229	55,349,938	29,751,504
	Banco Popolare di Sondrio	615,816	3,238	38,358,158	37,221,167	5,458,601
	Credito Emiliano	511,812	6,130	36,293,489	33,297,524	17,991,010
Luxembourg	BCEE	317,601	1,882	46,546,748	25,692,721	21,747,378
Malta	Bank of Valletta	141,769	1,823	12,078,640	5,151,051	4,201,563
Netherlands	ING Groep N.V.	3,563,424	56,196	732,801,588	689,823,680	233,967,117
	Cooperatieve Rabobank U. A	5,715,858	43,247	438,664,051	480,996,005	95,811,403
	ABN Amro Bank N.V.	1,916,520	17,977	287,600,473	300,626,294	82,874,331
	DE Volksbank NV	140,425	2,991	55,704,905	56,687,880	10,808,230
	NIBC Bank	43,813	667	14,427,824	20,049,317	2,833,214
Poland	PKO BP	1,169,655	27,708	69,696,392	60,655,920	23,809,410
	Bank Pekao	510,709	15,678	43,747,046	37,104,917	13,540,551
	Santander Bank Polska	451,028	13,642	42,789,831	37,760,387	13,426,821
Portugal	Banco Commercial Protugues	819,455	18,585	73,774,984	56,394,893	22,536,912
	Novo Banco	211,658	4,869	42,969,764	28,253,155	15,755,076
	Banco BPI	190,488	4,840	29,524,620	24,666,434	8,820,328

	Caxia Geral de Depositos	656,760	12,372	75,120,865	54,044,856	27,187,264
	Banco Santander Totta	423,065	4,444	47,302,764	44,194,752	9,580,206
Romania	Banca Transilvania	254,666	9,690	18,495,850	9,470,956	7,766,281
Slovenia	Nova Ljubljanska Banka	219,743	5,878	13,294,549	8,543,102	4,759,005
	BKS Bank AG	87,447	1,099	7,368,562	7,063,998	2,143,371
	Nova Kreditna Banka Maribor	74,567	1,364	4,657,090	3,125,384	1,442,180
Switzerland	UBS Group AG	12,803,000	68,601	508,460,000	339,430,000	490,063,000
	Credit Suisse Group AG	8,089,238	47,860	510,754,995	314,010,526	360,721,948
	Zürcher Kantonalbank	672,382	5,145	134,956,617	96,277,626	36,892,170
	Banque Cantonale Vaudoise	447,222	1,921	38,114,025	33,844,246	6,858,087
	Julius Baer Group	633,030	6,639	78,571,677	49,278,690	42,354,353
	Raiffeisen Schweiz	3,095,985	11,045	201,344,008	199,804,167	21,615,580
Spain	Banco Santander S.A.	38,489,926	196,419	1,157,168,130	1,053,100,861	404,030,757
	BBVA	11,028,416	126,973	495,268,800	430,773,291	253,790,631
	CaixaBank S.A.	5,521,510	35,736	272,354,814	249,754,255	145,789,216
	Banco del Sabadell	3,311,524	24,454	202,203,439	165,791,072	52,077,928
	Bankia	2,399,569	16,035	185,421,614	131,918,746	68,171,117
	Unicaja Banco	988,827	6,014	54,833,429	30,347,236	23,601,736
	Bankinter	599,846	8,531	72,723,038	66,472,430	18,365,166
	Abanca	1,091,628	6,033	55,785,383	41,332,215	15,057,289
	Ibercaja Banco	807,775	5,304	45,899,702	34,042,209	20,736,131

Sweden	Svenska Handelsbanken AB	714,570	12,548	131,603,560	245,412,233	44,374,415
	SEB	715,753	15,819	165,448,043	177,804,242	108,116,201
	SwedBank AB	599,185	15,218	123,930,940	172,661,274	61,232,028
	Resurs Bank	13,170	681	2,682,264	3,370,661	729,155
	United Kingdom	HSBC	14,702,000	235,000	1,763,392,000	1,041,299,000
	Barclays	5,513,654	80,800	856,873,315	409,048,329	862,098,297
	Lloyds Banking Group	12,532,345	70,083	630,106,240	591,834,761	391,876,222
	NatWest Group	6,466,275	62,900	576,209,679	429,003,507	388,679,825
	Standard Chartered PLC	6,220,000	84,398	489,961,000	271,064,000	352,757,000
	Nationwide Building Society	1,165,080	18,285	250,835,470	260,866,425	30,450,645
	Coventry Building Society	102,085	2,635	55,146,909	55,418,262	2,323,424
	Close Brothers	295,123	2,345	7,546,075	9,305,743	460,567
Norway	DNB ASA	1,695,102	8,617	139,477,561	183,974,941	59,297,608

Table 4.2 Input and Output data of the European Banks for the data envelopment analysis.

	Country	N. Of DMUs	Fixed assets	Number of employees	Deposits & short-term funding	Total Loans	Other earning assets
North	Belgium	3	1,756,595	15,061	126,333,763	105,830,606	75,674,692
	Czech R.	2	509,946	9,111	48,637,484	30,296,363	14,630,520
	Denmark	5	643,508	6,542	64,665,618	111,559,040	68,581,823
	Finland	3	957,886	13,898	123,397,998	156,644,265	77,825,247
	France	8	10,355,036	77,069	581,755,282	348,176,482	552,006,601
	Germany	8	2,155,382	26,304	254,283,522	206,841,785	268,554,211
	Ireland	3	712,984	7,399	68,061,929	60,537,397	25,157,042
	Luxembourg	1	317,601	1,882	46,546,748	25,692,721	21,747,378
	Nederland	5	2,276,008	24,215	305,839,768	309,636,635	85,258,859

	Switzerland	6	4,290,142	23,535	245,366,887	172,107,542	159,750,856
	Sweden	4	510,669	11,066	105,916,201	149,812,102	53,612,949
	UK	8	5,874,570	69,555	578,758,836	383,480,003	425,066,247
	Norway	1	1,695,102	8,617	139,477,561	183,974,941	59,297,608
South	Austria	4	1,569,681	25,951	116,015,386	96,654,172	40,406,742
	Cyprus	2	263,806	3,343	18,069,161	9,380,944	4,300,031
	Greece	3	1,352,323	10,248	55,933,916	40,330,155	14,122,868
	Italy	10	7,860,093	29,622	207,548,694	191,364,720	93,641,679
	Malta	1	141,769	1,823	12,078,640	5,151,051	4,201,563
	Hungary	4	403,268	12,197	19,260,158	6,306,105	8,338,371
	Poland	3	710,464	19,009	52,077,756	45,173,741	16,925,594
	Portugal	5	460,285	9,022	53,738,599	41,510,818	16,775,957
	Romania	1	254,666	9,690	18,495,850	9,470,956	7,766,281
	Slovenia	3	127,252	2,780	8,440,067	6,244,161	2,781,518
	Spain	9	7,137,669	47,277	282,406,483	244,836,923	111,291,107

Table 4.3 Mean value of input – output variables for each country

Table 4.2 presents the input and output data collected for the data envelopment analysis on European Banks; on the other hand, in table 4.3, the average values of the inputs and outputs of each country's banks included in the analysis were calculated. As seen in the first row, the countries' productivity are separated as north and south countries will be compared later with non-parametric tests.

4.3 OBTAINED RESULTS FOR EFFICIENCY ANALYSIS OF DMUs

4.3.1 Application of MaxDEA

This section will deploy all the analysis methods used and the results generated from this analysis. For banking efficiency in the literature, we can find several methods and tools to apply the efficiency analysis. Numerous programs can also be obtained for free on the web, allowing you to apply the DEA simply by entering the input and output data and indicating the type of

model to be solved. The limit of this software is encountered if you want to solve more complex models with particular shapes like those seen so far. Some of them set limits for the number of DMUs. With MaxDEA software, researchers can choose and apply the desired methods (whether CCR, BCC, or others) or types of RTS (returns to scale). Furthermore, I used R studio to apply some statistical tests to compare the efficiency of DMUs and different groups of DMUs.

First of all, it is necessary to properly organize the spreadsheet to proceed more accurately with efficiency calculation. The selection of inputs and outputs is a highly important issue since different variables on the selected data can completely change the analysis results. As we stated in chapter 2.3, there are different approaches for data selection; the most used approaches in the literature are production and intermediation. Under the production approach, deposits are treated as outputs because they are viewed as a service provided by a bank to its customers. On the other hand, the financial intermediation approach views banks as intermediaries that take deposits and make loans. In this case, we decided to use the intermediation approach for the data selection since we do not analyse the branches of each bank separately; in the analysis, on the contrary, our main target is Europe's leading banks.

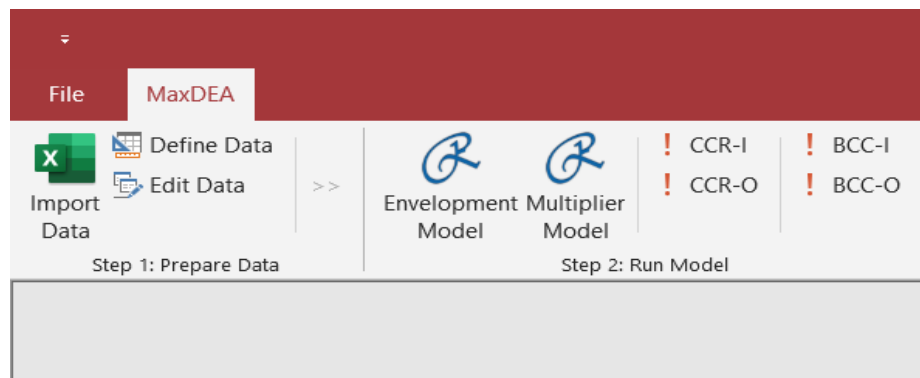


Figure 4.1 Imports of data in MaxDEA

As input data, we specified three inputs, namely, 'fixed assets,' number of employees,' and 'deposits and short-term funding'; on another side, 'total loans' and 'other earning assets' are used as outputs. After defining the input-output data, we have to import the data to use the MaxDEA program for analysis. Therefore, we press the section with the excel icon called "Import data" in figure 4.1 and select the excel file for analysis. After selecting the data, the next step will be to ensure that the program recognizes the data. For this, after the data have

been uploaded successfully, we need to click on the "define data" icon next to the "import data" icon. In the window that opens, we specify the names of the input and output values that we have previously determined and collected for each of the selected DMUs as "input" and "output." In our study, there are three input values and two output values. Later, in the "edit data" section, various changes are made to the optionally selected data.

The next step after selecting the data and naming them as input and output is to adjust the various parameters for the analysis of the data according to the researcher's request. For this purpose, when we click on the "envelopment model" icon in figure 4.1, the window specified in figure 4.2, which we have left below, will appear. Here it is possible to change many parameters required for data envelopment analysis. In the "Orientation" section, it can be determined whether the analysis is input or output-oriented. In input-oriented models, it is aimed to keep the output value constant and to minimize the input. In output-oriented analysis, the input is taken as one, and the output is maximized. In this study, the input value is tried to be minimized, so input-oriented analysis is performed. As seen in this section, it is possible to set more than the two most preferred choices we have mentioned.

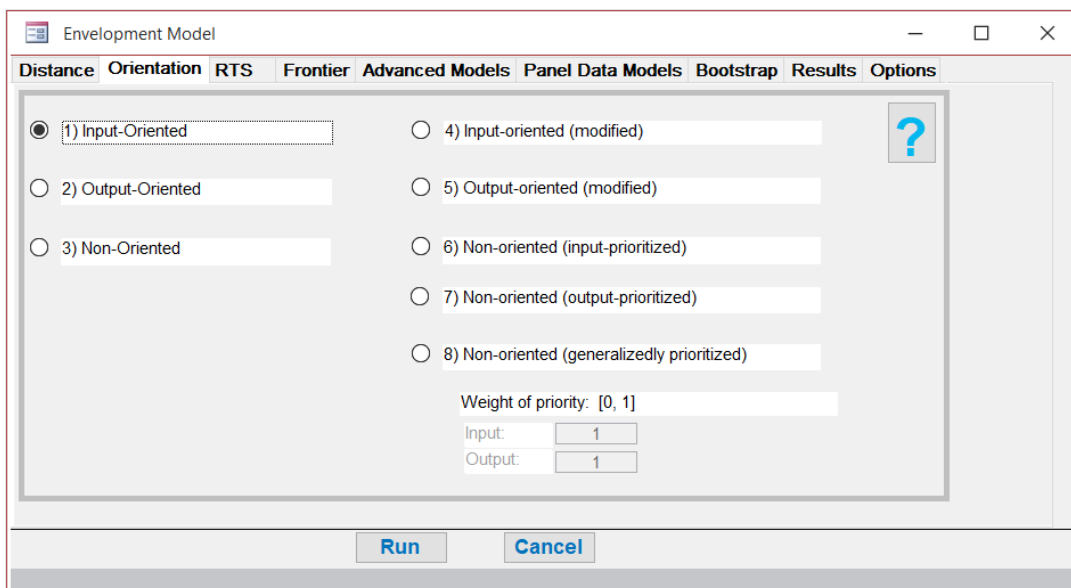


Figure 4.2 Defining the analysis parameters in MaxDEA

In another part, the returns to scale can be determined. Here, the analysis of the model as constant returns to scale or variable returns to scale can be set. Furthermore, to adjust various parameters, changes can be made within other sections, and different results can be obtained. Finally, we can get the analysis results by clicking the "run" button in figure 4.2. As you can

see, “MaxDEA” is a program that is not difficult to understand and has no DMU limit for analysis, so we made our choice in this direction.

4.3.2 Application of R studio and codes used

Another program widely used for DEA analysis is R Studio. One of the disadvantages of R studio is that some complex codes have to be written to perform analysis. However, it is possible to use R studio efficiently for various analyses, including DEA. In this thesis, since I have used R studio and MaxDEA to perform productivity analysis, I will write the steps I followed and the codes I used to perform the analysis successfully.

For DEA analysis in the R software, I will be using a package called “Benchmarking,” as seen in figure 4.3 left-bottom side, and also, I loaded the “psych” package, which we do not need for benchmarking but for some basic statistics. After loading the packages, as a next step, we have to load the data. For this, we can use ‘import dataset’> ‘from excel.’ or from another software, we can drop data. On another side, we can define the exact path of the data file and just run the code to load the data. The following codes show the packages we have used and how to define the data.

```
library(Benchmarking) #for DEA
library(psych) #for basic statistics
data<- read.csv("C:/Users/Dropbox/MY PC/deadata.csv") #define your data path
summary(data)
```

Following codes are for reading the uploaded data by the software:

```
describe(data$fixedassets)
describe(data$numberofemployees)
describe(data$deposits)
describe(data$totalloans)
describe(data$otherearningassets)
```

Project: (None)

Environment: Global Environment

History: Import Dataset

Connections: Tutorial

Data

Variable	Value
bcc	List of 12
data	102 obs. of 7 variables
s1	List of 10
x	num [1:102, 1:3] 2953696 1716321 444866 1163842 4529224 ...
y	num [1:102, 1:2] 1.78e+08 1.02e+08 3.46e+07 7.11e+07 1.75e+08 ...

```

1
2
3 library(Benchmarking) #for DEA
4 library(psych) #for basic statistics
5 data<- read.csv("c:/Users/Dropbox/MY PC/deadatafull1.csv") #define your data path
6 summary(data)
7
8 describe(data$fixedassets)
9 describe(data$numberofemployees)
10 describe(data$deposits)
11 describe(data$totalloans)
12 describe(data$otherearningsassets)
13
14
15 ##data properties
16 class(data)
17 str(data)
18
19
20 #input output selection #update your input and output variables names accordingly
21 x<- with(data, cbind(fixedassets,numberofemployees,deposits))
22 y<- with(data, cbind(totalloans,otherearningsassets))
23
24 #calculating efficiency
25 #####
26 #variable returns to scale
27 bcc<-dea(x,y, RTS=VRS, ORIENTATION="in") #for output oriented simply update ORIENTATION="out"
28 bcc
29 Shapiro.test(bcc$eff) #to check normality
30
31 eff(bcc)
32 data.frame(bcc$eff)
42:1 (untitled)

```

Console

```

~/
> library(Benchmarking) #for DEA
> library(psych) #for basic statistics
> summary(data)
  ...1      DMU      Length:102      numberofemployees      deposits      totalloans
Min.   : 1.00   Class :character Min.   : 13170   Min.   :2.682e+06   Min.   :3.123e+06
1st Qu.: 26.25  Mode  :character 1st Qu.: 349738 1st Qu.:4.048e+07 1st Qu.:3.295e+07
Median : 51.50  Mean  :character Median : 712964  Median :7.971e+07  Median :7.179e+07
Mean   : 51.50  Mean  :28375   Mean   :2.789e13  Mean   :2.171e+08  Mean   :1.719e+08
3rd Qu.: 76.75  3rd Qu.:2214205 3rd Qu.: 32978 3rd Qu.:2.504e+08 3rd Qu.:2.357e+08
Max.   :102.00  Max.   :442110838 Max.   :235000  Max.   :1.763e+09  Max.   :1.053e+09
otherearningsassets
Min.   :4.606e+05
1st Qu.:1.245e+07
Mean   :2.967e+07
3rd Qu.:1.458e+08
Max.   :1.372e+09
> describe(data$fixedassets)
vars n mean sd median trimmed mad min max range skew kurtosis se
X1 1.102 2789813 6293663 712964 1380163 801687 13170 442110838 44197668 4.78 25.91 623165.5
> describe(data$numberofemployees)
vars n mean sd median trimmed mad min max range skew kurtosis se
X1 1.102 28374.98 43392.3 10222.5 18591.06 11373.02 469 235000 234531 2.64 7.38 4316.28

```

User Library

Name	Description	Version
<input type="checkbox"/> abind	Combine Multidimensional Arrays	14-5
<input type="checkbox"/> askpass	Safe Password Entry for R, Git, and SSH	1.1
<input type="checkbox"/> assertthat	Easy Pre and Post Assertions	0.2.1
<input type="checkbox"/> backports	Remplementations of Functions Introduced Since R-3.0.0	1.1.10
<input type="checkbox"/> base64enc	Tools for base64 encoding	0.1-3
<input checked="" type="checkbox"/> Benchmarking	Benchmark and Frontier Analysis Using DEA and SFA	0.29
<input type="checkbox"/> BH	Boost C++ Header Files	1.75b-0
<input type="checkbox"/> bibliometrix	Comprehensive Science Mapping Analysis	3.04
<input type="checkbox"/> bibliometrxData	Bibliometrix Example Datasets	0.1.0
<input type="checkbox"/> bitops	Bitwise Operations	1.0-6
<input type="checkbox"/> BMA	Bayesian Model Averaging	3:18.12
<input type="checkbox"/> broom	Convert Statistical Objects into Tidy Tibbles	0.7.5
<input type="checkbox"/> bslib	Custom 'Bootstrap' Sass Themes for 'shiny' and 'markdown'	0.2.4
<input type="checkbox"/> cachem	Cache R Objects with Automatic Pruning	1.0.3
<input type="checkbox"/> callr	Call R from R	3.5.1
<input type="checkbox"/> car	Companion to Applied Regression	3.0-10
<input type="checkbox"/> carData	Companion to Applied Regression Data Sets	3.0-4
<input type="checkbox"/> cell Ranger	Translate Spreadsheet Cell Ranges to Rows and Columns	1.1.0
<input type="checkbox"/> checkmate	Fast and Versatile Argument Checks	2.0.0
<input type="checkbox"/> chron	Chronological Objects which can Handle Dates and Times	2.3-56
<input type="checkbox"/> cli	Helpers for Developing Command Line Interfaces	2.1.0
<input type="checkbox"/> clipr	Read and Write from the System Clipboard	0.7.1
<input type="checkbox"/> colorspace	A Toolbox for Manipulating and Assessing Colors and Palettes	1.4-1

Figure 4.3 R Studio front page to apply analysis

Afterward, writing simple codes, we can view the class of the data as well as the structure of the data. Subsequently, to make the analysis possible, we must define our inputs and outputs, so we define our input as ‘x’ and output as ‘y’, as in the following box.

```
#data properties #input output selection #update your input and output variables names accordingly
class(data)
str(data)
x<- with(data, cbind(fixedassets,numberofemployees,deposits))
y<- with(data, cbind(totalloans,otherearningassets))
```

To do the DEA analysis, we need to specify some parameters in the R software, as we did for the MaxDEA program in section 4.3.1. First, we determine whether the analysis has a constant return to scale or a variable return to scale, and then we specify whether the model should be input-oriented or output-oriented. For this, we simply need to write the following codes in order.

```
#constant returns to scale #input oriented
ccr<-dea(x,y, RTS="crs", ORIENTATION = "in") #for output oriented simply update ORIENTATION =
"out"
ccr
```

```
eff(ccr)
data.frame(bcc$eff)
summary(bcc)
sl<-slack(x,y,bcc)
data.frame(eff(bcc),eff(sl),sl$slack,sl$slsx,sl$slsy,lambda(sl))
```

We are able to view the efficiency scores with ‘eff(ccr)’ command, and for the efficiency score in a data frame structure, writing the ‘data.frame(ccr\$eff)’ command.

4.3.3 Results obtained for analysis

After talking about the input and output data and sharing the basic statistical data about them, the results of the analysis are shown in table 4.4. A mirror to our work, Henriques et al. (2018), while analyzing banks in efficiency analysis on Brazilian banks, two different models were

applied with the same data, and the models were compared. Therefore, in our study, we tried to apply the two most used models in data envelopment analysis. For this, we have placed the analysis results of two models developed by Charnes, Cooper, and Rodhes (1978) and Banker, Charnes, and Cooper (1984) for each bank in table 4.4. In addition, the scale efficiency was also calculated for each bank in order to be a suitable indicator for comparison. Based on the CCR and BCC model, we can define the scale efficiency as follows:

Let the CCR and BCC scores of a DMU be θ_{CCR}^* and θ_{BCC}^* , respectively. The scale efficiency defined by (Cooper, Seiford, and Tone, 2007) is:

$$SE = \frac{\theta_{CCR}^*}{\theta_{BCC}^*}. \quad 4.7$$

Table 4.4 Obtained results of the analysis on selected banks

Countries	DMU	BCC Scores	CCR Scores	Scale Efficiency
Austria	Erste Group Bank	0.1993	0.1969	0.9878
	Raiffeisen Bank International AG	0.1848	0.1796	0.9720
	BAWAK P.S.K.	0.2716	0.2108	0.7762
	Unicredit Bank Austria AG	0.3227	0.2805	0.8692
Belgium	KBC Group NV	0.1720	0.1628	0.9467
	Belfius Bank SA/NV	0.4121	0.3899	0.9459
	Argenta	1	1	1
Cyprus	Bank of Cyprus Public Company	0.2384	0.1379	0.5785
	Hellenic Bank Public Company	0.2267	0.0959	0.4229
Czech Republic	Ceska Sporitelna a.s.	0.1628	0.1381	0.8485
	Komercni Banka	0.2038	0.1694	0.8312
Denmark	Danske Bank A/S	0.8097	0.3685	0.4550
	Nykredit A/S	1	1	1
	Jyske Bank	0.6235	0.5564	0.8924

	DMU	BCC Scores	CCR Scores	Scale Efficiency
	Sydbank	0.3399	0.1818	0.5349
	Spar Nord Bank	0.4341	0.1846	0.4253
Finland	Nordea Bank Abp	1	0.3305	0.3305
	OP Financial Group	0.3012	0.2920	0.9697
	AlandsBanken	1	0.2853	0.2853
France	Bnb Paribas	1	1	1
	Credit Agricole	1	1	1
	Societe generale	0.9717	0.8452	0.8698
	Groupe BPCE	0.4812	0.4788	0.9950
	Credit Mutuel Group	1	0.6862	0.6862
	La Banque Postale SA	0.7531	0.7485	0.9939
	Banque Palatine	0.5565	0.2499	0.4490
	Credit du Nord	0.2042	0.1823	0.8928
Germany	Deutsche Bank AG	0.8616	0.3176	0.3686
	DZ Bank AG	0.4648	0.4499	0.9679
	Commerzbank AG	0.4779	0.1917	0.4010
	KFW Bankgruppe	1	1	1
	HypoVereinsbank	0.3397	0.3339	0.9830
	Landesbank Baden-Wurttemberg	0.4258	0.4233	0.9942
	Bayerische Landesbank	0.4226	0.4225	0.9999
	Landesbank Hessen-Thüringen	0.4925	0.4764	0.9674
Greece	Piraeus Bank SA	0.1835	0.1645	0.8967
	National Bank of Greece	0.1666	0.1267	0.7606

	DMU	BCC Scores	CCR Scores	Scale Efficiency
	Alpha Bank	0.1930	0.1729	0.8959
Hungary	OTP Bank	0.0694	0.0486	0.7006
	K&H Bank	0.3126		0.3930
	Erste Bank	0.3853	0.1618	0.4200
	CIB Bank	0.4844	0.1390	0.2871
Ireland	Bank of Ireland Group plc (BOI)	0.2383	0.2220	0.9315
	Allied Irish Bank	0.2182	0.2018	0.9247
	Ulster Bank Ireland	0.4234	0.2746	0.6486
Italy	Intesa Sanpaolo	0.8926	0.2053	0.2300
	UniCredit	0.8503	0.1888	0.2221
	CDP Group	0.6675	0.2303	0.3450
	Banco BPM	0.2151	0.2115	0.9834
	Banca Monte dei Paschi di Siena	0.1837	0.1791	0.9749
	Banca Nazionale del Lavoro	0.2085	0.1894	0.9084
	BPER Banca	0.2107	0.1982	0.9407
	Mediobanca	0.3544	0.3256	0.9188
	Banco Popolare di Sondrio	0.3189	0.2488	0.7803
	Credito Emiliano	0.2477	0.2120	0.8561
Luxembourg	BCEE	0.5087	0.3458	0.6798
Malta	Bank of Valletta	0.3164	0.1018	0.3217
Netherlands	ING Groep N.V.	1	0.2485	0.2485
	Cooperatieve Rabobank U. A.	0.9918	0.2694	0.2717
	ABN Amro Bank N.V.	0.8013	0.3147	0.3927

	DMU	BCC Scores	CCR Scores	Scale Efficiency
	DE Volksbank NV	0.4275	0.3383	0.7912
	NIBC Bank	1	0.5212	0.5212
Poland	PKO BP	0.2085	0.1941	0.9314
	Bank Pekao	0.2326	0.2027	0.8712
	Santander Bank Polska	0.2453	0.2142	0.8733
Portugal	Banco Commercial Protugues	0.1996	0.1841	0.9221
	Novo Banco	0.2555	0.2113	0.8272
	Banco BPI	0.2678	0.2152	0.8037
	Caxia Geral de Depositos	0.1955	0.1792	0.9167
	Banco Santander Totta	0.2850	0.2328	0.8167
Romania	Banca Transilvania	0.2008	0.1189	0.5921
Slovenia	Nova Ljubljanska Banka	0.2552	0.1438	0.5636
	BKS Bank AG	0.5639	0.2284	0.4051
	Nova Kreditna Banka Maribor	0.5835	0.1512	0.2591
Switzerland	UBS Group AG	0.6276	0.1591	0.2534
	Credit Suisse Group AG	0.4925	0.1888	0.3835
	Zürcher Kantonalbank	0.4084	0.3751	0.9185
	Banque Contonale Vauoise	0.4706	0.3169	0.6733
	Julius Baer Group	0.2332	0.2007	0.8605
	Raiffeisen Schweiz	0.3141	0.3136	0.9985
Spain	Banco Santander S.A.	1	0.1849	0.1849
	BBVA	0.7401	0.1811	0.2447
	CaixaBank S.A.	0.4679	0.2056	0.4394

	DMU	BCC Scores	CCR Scores	Scale Efficiency
	Banco del Sabadell	0.1900	0.1890	0.9952
	Bankia	0.1868	0.1813	0.9707
	Unicaja Banco	0.1786	0.1317	0.7373
	Bankinter	0.2447	0.2293	0.9371
	Abanca	0.2200	0.1771	0.8051
	Ibercaja Banco	0.2270	0.1736	0.7646
Sweden	Svenska Handelsbanken AB	0.8699	0.4879	0.5609
	SEB	0.3904	0.3891	0.9965
	SwedBank AB	0.3696	0.3679	0.9953
	Resurs Bank	1	0.3314	0.3314
United Kingdom	HSBC	1	0.2356	0.2356
	Barclays	0.7356	0.3328	0.4524
	Lloyds Banking Group	0.9972	0.2225	0.2232
	NatWest Group	0.7120	0.1850	0.2598
	Standard Chartered PLC	0.3676	0.1607	0.4372
	Nationwide Building Society	0.5435	0.2765	0.5087
	Coventry Building Society	0.4927	0.3646	0.7401
	Close Brothers	0.4635	0.2133	0.4601
Norway	DNB ASA	0.4158	0.4131	0.9937

The CCR model assumes the constant returns-to-scale production possibility set, i.e., it is postulated that a reduction of all observed DMUs and their nonnegative combinations are possible, and hence the CCR score is called '*global technical efficiency*'. On the other hand, the BCC model assumes that convex combinations of the observed DMUs form the production

possibility set, and the BCC score is called *local pure technical* efficiency (Cooper, Seiford, and Tone, 2007).

Accordingly, if the bank, which is the decision-making unit in the sample, has reached the maximum efficiency level in the results obtained in both BCC and CCR models, then we know that it has reached the most efficient and highest *scale efficiency* for this bank. However, if the efficiency level of the bank is high according to the BCC model, but the inefficiency value is high according to the CCR model, then we can say that this decision-making unit is only *locally pure technical* efficient, but not *global technical* efficient due to its scale size. When we look at the results we have obtained, it is possible to see an effective inefficiency table for both models in the majority of banks, although the efficiency rate in the BCC model is slightly higher than in the other model. As mentioned above, according to the results of both models used for analysis, only 5 of the 102 DMUs reached the maximum *scale efficiency* level. These were 'Argenta', 'Nykredit A / S', 'BNB Paribas', 'Credit Agricole', and 'KFW Bankgruppe'. At the same time, we can state that these banks have achieved the highest productivity rates both globally and locally.

However, we can view the high inefficiency rates of all four Austrian banks included in the analysis, with average efficiency rates between 0.19 and 0.32 in both models. For example, in Finland, two out of three banks have the highest efficiency rate of 1 for the BCC model, but for the CCR model, this ratio is around 0.33 and 0.28. When we pay attention to the French banks, we can observe that the overall efficiency rate is higher than in other countries, as two of the nine French banks achieved the highest *scale efficiency* level in both models, while the other 'Credit Mutuel Group' bank has an efficiency rate of 1 for the BCC model and efficiency rate of 0.68 for CCR model. The other two 'Societe Generale' and 'La Banque Postale SA' banks have efficiency ratios at 0.9 and 0.8 levels in both models. Since we will talk about the average productivity of the countries included in the analysis in the future, we are only evaluating the results of banks for now.

When we look at Italian banks, we can only observe *local technical efficiency* in the first three largest banks together with a general inefficiency table. In 'Intesa Sanpaolo', 'Unicredit', and 'CDP Group' banks the efficiency ratios are 0.89, 0.85, 0.67 respectively, for the BCC model. However, as we just mentioned, according to the results of the remaining seven banks, both models show a high level of inefficiency. One of the examples showing local efficiency similar to this is the Netherlands. While four of the five Netherlands banks we have included

in the analysis are locally highly efficient, their *global technical* efficiency ratios range from 0.24 to 0.52. On the other hand, the efficiency ratios of *local pure technically* efficient banks, 'ING Groep N.V.', 'Cooperative Rabobank,' 'ABN Amro Bank,' 'NIBC Bank', were 1, 0.99, 0.80, and 1, respectively.

Although the *local* efficiency rates are high in four banks in the UK, including *HSBC*, one of the largest banks in Europe, the results of the CCR model, i.e., the *global technical* efficiency rates are very low, on average between 0.19 - 0.33. The ratios of the four banks 'HSBC', 'Barclays,' 'Lyods Banking Group,' 'NatWest Group,' which are efficient according to the BCC model, are 1, 0.73, 0.99, 0.71, respectively.

In general, according to the measurement results of the BCC model, the efficiency rate of selected banks for 2019 is 48%, while this rate is lower in the CCR model, only 30%. In the light of these results, we can say that the European banks are highly inefficient in general. After interpreting the DEA analysis of banks with two different models developed by Charnes, Cooper, and Rodhes (1978) and Banker, Charnes, and Cooper (1984), we will now try to compare their efficiency rates on the basis of countries rather than the overall effectiveness of decision-making units. We will try to determine which of the country is more efficient. To do this, we calculate the average productivity rates of the banks of each country for two different models and rank them by comparing the efficiency rates taken within them. Of course, we may not get accurate results only with this table, so we will compare different groups of DMUs by applying non-parametric tests; these tests are: 'Mann Whitney test' and 'Kolmogorov-Smirnov test.'

Table 4.5 includes the mean efficiency rates of the banks included in the analysis and their rankings among themselves according to these rates. However, since the number of banks included in the analysis is not the same for all countries, the average productivity of some countries is determined by only one bank, for Norway, Romania, Malta, and Luxembourg. When we look at the table, according to the BCC model results, the first three countries with the highest average efficiency rate are Netherland, Finland, and France, respectively. On the other hand, the top three countries with the highest mean efficiency rates for the CCR model results were France, Belgium, and Denmark, respectively. Here, France ranks in the top three for both models, showing that the average efficiency of France is high compared to the others. However, the point to note here is that since the efficiency rates of the BCC model are high,

the efficiency ratios of the highest efficiency DMUs are 0.85, while this figure starts from 0.65 in the other.

Country	N. Of DMUs	Mean Efficiency (BCC)	Ranking (BCC)	Mean Efficiency (CCR)	Ranking (CCR)
Austria	4	0.2446	18	0.2169	14
Belgium	3	0.5280	8	0.5176	2
Cyprus	2	0.2325	20	0.1169	23
Czech R.	2	0.1833	23	0.1538	20
Denmark	5	0.6414	6	0.4583	3
Finland	3	0.7671	2	0.3026	9
France	8	0.7458	3	0.6489	1
Germany	8	0.5606	7	0.4519	4
Greece	3	0.1810	24	0.1547	19
Hungary	4	0.3129	16	0.1181	22
Ireland	3	0.2933	17	0.2328	12
Italy	10	0.4149	13	0.2189	13
Luxembourg	1	0.5087	9	0.3458	7
Malta	1	0.3164	15	0.1018	24
Niderland	5	0.8441	1	0.3384	8
Poland	3	0.2288	21	0.2037	16
Portugal	5	0.2407	19	0.2045	15
Romania	1	0.2008	22	0.1189	21
Slovenia	3	0.4676	10	0.1745	18
Switzerland	6	0.4244	11	0.2590	10
Spain	9	0.3839	14	0.1837	17
Sweedden	4	0.6575	5	0.3941	6
United Kingdom	8	0.6640	4	0.2489	11
Norway	1	0.4158	12	0.4131	5

Table 4.5 Mean efficiency of DMUs by country

At the same time, the rankings of the countries in the results for the BCC model are not exactly the same for the CCR model. However, the efficiency rates of the BCC model are always higher than the CCR model in the analysis performed on the same DMU.

4.4 RESULTS OF APPLIED NON-PARAMETRIC TESTS TO COMPARE THE GROUP OF DMUs

4.4.1 Non-parametric tests to compare the efficiency of two groups of DMUs

Comparing efficiency results obtained from analysed data only with their average rates may not be significant. For this reason, we will test whether our results are empirically significant by applying non-parametric tests. To do this, we will perform empirical measurements through statistical tests developed by Banker et al. (2010). Thanks to these tests, the statistical properties of the DEA estimators are now established, identifying the conditions under which they are consistent and of maximum likelihood. Non-parametric tests are widely used in the DEA literature, and most of these tests are based on order statistics. We can specify the non-parametric tests we will use in this study as the "Mann-Whitney test" and "Kolmogorov-Smirnov test." In this section, we will share the statistical characteristics and general application stages of these tests.

4.4.1.1 Mann – Whitney test

The Mann-Whitney test is a method that measures whether one of the samples selected between two groups compared is stochastically larger than the other. This test generally is the same as other non-parametric tests; that is, if the null hypothesis is accepted, it means that both groups have the same probability distribution, on the other hand, if the null hypothesis is rejected, it means that one of the samples of the compared groups has more extensive observations than the other.

For the problem considered here, the Mann-Whitney statistic is defined as the number of times \hat{u}_i precedes \hat{u}_j in the ordered sample of two groups, $i = 1 \dots N_1$ and $j = 1 \dots N_2$. For this, let's set the random variables:

$$\hat{D}_{ij} = \begin{cases} 1 & \hat{u}_i < \hat{u}_j \\ 0 & \text{otherwise.} \end{cases} \quad 4.5$$

Then the Mann - Whitney U statistic test would be written in this way:

$$\hat{U} = \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} \hat{D}_{ij} \quad 4.6$$

When the N_1 and N_2 samples of the compared groups are large, U is distributed normally, and it can be written as $N_1 \frac{N_2}{2}$ and its variance as $N_1 \times N_2 \frac{N+1}{12}$. Based on all this, standard normal distribution tests with large samples are formulated in this way:

$$Z = \frac{\hat{U} - N_1 N_2 / 2}{\sqrt{N_1 \times N_2 \times (N+1) / 12}} \quad 4.7$$

One of the points to be noted here is that if the inefficiency and noise variables u_m and v are independent, \hat{u}_m which is the order of the DEA estimate, it will be consistent with the true order of u_m , and consequently, the Mann - Whitney test will remain consistent. One of the best advantages of R studio is that we do not need to write lots of codes to run the Mann - Whitney test, but we can still view the codes used below.

```
wilcox.test(x, y)
Wilcoxon rank sum test with continuity correction
data: x and y
W = 1164, p-value = 0.3622
alternative hypothesis: true location shift is not equal to 0
```

4.4.1.2 Kolmogorov – Smirnov test

Unlike the two tests we mentioned above, the Kolmogorov - Smirnov test has the advantage of collectively considering distribution functions. While the primary purpose in other tests is to determine the difference between the two means or medians, it can be used as a goodness of fit test, and an underlying probability distribution can be applied to see if it differs from a hypothesized distribution.

The Kolmogorov - Smirnov test calculates the maximum vertical distance between the empirical distributions of \tilde{u} , $F^1(\hat{u}_1)$ and $F^2(\hat{u}_2)$ for the two groups compared. Another difference of this test is that it takes a value between 0 and 1. When the value is close to 0, it indicates no big differences in inefficiency between the two tested groups, while the higher value indicates that there are high differences in inefficiency between the groups. Therefore since the order of \hat{u}_m is consistent with u_m , \hat{D} is consistent with the true D estimated from u_m . The Kolmogorov-Smirnov test, which is denoted as \hat{D} , is derived from \hat{u}_m . Accordingly, we can depict the distributed \hat{D} , asymptotically, as follows:

$$\lim_{N_1, N_2 \rightarrow \infty} P \left(\sqrt{\frac{N_1 N_2}{N_1 + N_2}} \hat{D} \leq Z \right) = 1 - e^{-2Z^2} \quad 4.8$$

```

ks.test(x, y)
Two-sample Kolmogorov-Smirnov test
data: x and y
D = 0.31373, p-value = 0.01321
alternative hypothesis: two-sided
Warning message:
In ks.test(x, y): cannot compute exact p-value with ties

```

4.4.2 Results of compared DMUs by regions of Europe and number of employees

Although the results we obtain in table 4.5 show us the mean efficiency rates of the countries, we will also compare two different groups of countries with non-parametric tests. There are two different criteria for formulating groups; first is dividing DMUs for the number of employees, second, dividing DMUs as northern and southern countries. In the first comparison, from 102 DMUs, 51 are the biggest for their number of employees, and the other 51 banks are the smallest for their number of employees. Along with this, at the second comparison, we include the following countries' banks in the northern group: Finland, Sweden, Norway, UK, Ireland, Denmark, Germany, Poland, Netherlands, Belgium, Czech Republic, Luxembourg, France, Switzerland, and following countries' banks in the southern group: Malta, Greece, Cyprus, Spain, Portugal, Italy, Romania, Austria, Hungary, Slovenia.

When measuring the efficiency of two groups, only comparing their mean efficiency can sometimes lead to incorrect measurements, or some people may have questions about the accuracy of the results. However, thanks to the works of Banker (1993) and Banker et al. (2010), the statistical properties of the DEA estimators are now established, identifying the conditions under which they are consistent and of maximum likelihood. To address these questions, we will apply two non-parametric tests to compare the groups. As can be seen, the test results described in table 4.6 were applied to verify the null hypothesis of the distributions of the populations from which the two groups were derived. The null hypothesis is that both groups were sampled from populations with identical distributions. The null hypothesis is rejected for extremely large or small values as the two samples come from homogeneous populations relative to the median. Accordingly, the test will be two-tailed; consequently, the p-value must be less than 0.025 or 0.005 or greater than 0.975 or 0.995, depending on whether the significance level chosen is 5% or 1%.

Non-parametric Tests	Test Statistics	P-value
Mann-Whitney u Test	1164	0.3622
Kolmogorov-Smirnov Test	0.31373	0.01321

Table 4.6 applied non-parametric test results for number of employees

Applying more than one test allows us to draw more confident and complete conclusions about the results of comparisons of different DMUs. As you can see from the tests, there is no univocal answer. When we look at the table, the p-value of the KS test is smaller than 0.05 with a p-value of 0.01321, i.e., rejects the null hypothesis at a confidence level of 5%; however, with 0.3622 p-value Mann-Whitney test accepts the null hypothesis. Although another test result seems to have to accept H_0 , it should be noted that the Kolmogorov-Smirnov test is more powerful than the other non-parametric tests used here for not too numerous samples, and therefore to be preferred. For this reason, it has been concluded that in the DMU groups, according to the number of employees, bigger is outperforming the smaller.

Non-parametric Tests	Test Statistics	P-value
Mann-Whitney u Test	545	1.155e-06
Kolmogorov-Smirnov Test	0.5381	1.223e-06

Table 4.7 Applied non-parametric test results for northern and southern countries

In table 4.7, non-parametric tests were applied to the groups of DMUs between northern and southern countries' banks. When we look at table 4.7, the p-value of both tests is quite smaller than the confidence level of 5%, so based on these results, we can absolutely conclude that northern countries' banks operate more efficiently than and outperform southern countries' banks. In our analysis, there are exactly 102 banks from 24 different countries in the European Union. Of course, we do not have the opportunity to test separately for each country's groups, so we made groups of countries according to different criteria, and non-parametric tests were applied.

CONCLUSION

I want to write a general conclusion about the work we have done in this part of our thesis. In this study, the general purpose is to perform an efficiency analysis of selected banks according to the total assets of the European Union. The most widely used non-parametric data envelopment analysis method in the literature was adopted to perform this assessment. In contrast to parametric methods that require the ex-ante specification of a production- or cost function, non-parametric approaches compare feasible input and output combinations based on the available data only. Since the majority of decision-making units are large and involved in financial intermediation activities, an intermediation approach has been used in data selection in order to obtain appropriate results from the analysis. For this reason, it is necessary to make a careful input-output selection in order to get effective results.

Input-oriented BCC and CCR models were adopted simultaneously for the analysis performed on 112 banks that show merit in the European Union. The reason for using both models is because there is no consensus in the literature on which model is best for evaluating financial institutions. Using the two models at the same time gives us more robust conclusions about the cause of the inefficiencies of decision-making units. European banks' data for 2019 were used to conduct the data envelopment analysis.

Based on the results obtained, it is possible to say that the majority of the banks operating in the European Union have a high degree of inefficiency. In general, even if different results are obtained from BCC and CCR models, the efficiency rates of DMUs are low even in the BCC model. Only five of the 112 DMUs included in the analysis were found to have full-scale efficiency. Considering the large number of DMUs, the efficiency of a plain five banks is far below the average; in other words, only 4.5% of the analyzed banks have scale efficiency.

In this study, although the banks are examined separately, the efficiency of the banks has been tried to be compared among the countries. The average BCC and CCR efficiency of DMUs in the compared countries, as well as the *scale efficiencies*, are also included in the table. *Scale efficiency* is obtained by dividing the CCR model results by the BCC model results. Although

there is a general inefficiency among the countries after the evaluation of the results, there are a few countries, such as France, where the average productivity is high. It is possible to mention the names of countries such as France, Sweden, Germany, Denmark, and Belgium as examples. The average *scale efficiency* of these countries listed above is higher compared to others. However, although countries such as UK, Netherlands, and Finland have high *local technical efficiency* rates in the BCC model, *global technical efficiency* rates in the CCR model remained below the average. It should be noted that the countries with high productivity rates are generally northern European countries. In other words, the overall productivity rates of banks in north European countries are higher than those of banks in Mediterranean countries and east European countries.

BIBLIOGRAPHY

AFRIAT, S.N., “Efficiency estimation of production functions,” *International Economic Review*, Vol.13, (1972).

APOSTOLOS G. CHRISTOPOULOSA, IOANNIS G. DOKASB, SOFIA KATSIMARDOUB, ELEFThERIOS SPYROMITROS, “Assessing banking sectors’ efficiency of financially troubled Eurozone countries,” *Research in International Business and Finance* 52 (2020)

BANKER, R.D. AND R.M. THRALL, “Estimation of returns to scale using data envelopment analysis,” *European Journal of Operational Research*, Vol.62, (1992).

BANKER, R.D., A. CHARNES, AND W.W. COOPER, “Some models for estimating technical and scale inefficiencies in data envelopment analysis,” *Management Science*, Vol.30, (1984), pp.1078-1092.

BAUER, PAUL W., ALLEN N. BERGER, GARY D. FERRIER, DAVID B. HUMPHREY, “Consistency Conditions for Regulatory Analysis of Financial Institutions: A Comparison of Frontier Efficiency Methods”, *Journal of Economics and Business*, (1998).

BERGER, A.N., D.B. HUMPHREY, “Efficiency of financial institutions: International survey and directions for future research,” *European Journal of Operational Research*, Vol.98, (1997), pp.175-212.

BOLES, J.N., “Efficiency squared - efficiency computation of efficiency indexes,” *Proceedings of the 39th Annual Meeting of the Western Farm Association*, (1966). pp.137-142.

BROUSSEAU, E., GLACHANT, M., “The economics of contracts: theories and applications,” London: *Cambridge University Press*, (2002).

Bureau Van Dijk, Orbis Database

<https://orbis.bvdinfo.com/version2021521/orbis/1/Companies/Search>

CÂNDIDA FERREIRA, “Evaluating the European bank efficiency using Data Envelopment Analysis: evidence in the aftermath of the recent financial crisis,” *R.E.M. – Research in Economics and Mathematics* (2019)

CASU, B. AND GIRARDONE, C., “A comparative study of the cost efficiency of Italian bank conglomerates”, *Managerial Finance*, Vol. 28 No. 9, (2002), pp. 3-23.

CHARNES, ALAN., COOPER, W.W., RHODES, “Measuring the efficiency of decision-making units”, *European Journal of Operational Research* 2, (1978).

CHORTAREAS, G., GIRARDONE, C., VENTOURI, A., “Financial freedom and bank efficiency: evidence from the European Union,” *Journal of Banking and Finance* 37 (4), (2013), 1223–1231.

CHORTAREAS, G.E., GIRARDONE, C., VENTOURI, A., “Bank supervision, regulation, and efficiency: evidence from the European Union,” *Journal of Financial Stability*, 8 (4), (2012) 292–302.

CHRIS STEWART, ROMAN MATOUSEK, THAO NGOC NGUYEN, “Efficiency in the Vietnamese banking system: A DEA double bootstrap approach,” *Research in International Business and Finance* 36 (2016) 96–111

CINGI SELÇUK, ARMAĞAN TARIM, “Türk Banka Sisteminde Performans Ölçümü Dea-Malmquist TFP Endeksi Uygulaması”, *Türkiye Bankalar Birliği Araştırma Tebliği Serisi, Sayı:2000-01*, (2000)

COASE, R., “The problem of social cost”, *Journal of Law and Economics*, 3 (1), (1960), 1-44. ss.

COELLI, T., D.S.P. R.A.O., AND G.E. BATTESE, “An Introduction to Efficiency and Productivity Analysis,” *Kluwer Academic Publishers: Boston*, (1998).

CONLISK, J., “Bounded rationality and market fluctuations”, *Journal of Economic Behaviour and Organization*, 29 (2), (1996), 233-250. ss.

COOPER, WILLIAM W.; SEIFORD, LAWRENCE M.; TONE, KAORU, “Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software (2 ed.)”, *Springer US*, (2007).

CVILIKAS, A., JURKONYTE - DUMBLIAUSKIENE, E., “Assessment of Risk Management Economic Efficiency Applying Economic Logistic Theory,” *Transformations in Business & Economics*, Vol. 15, no 3 (39), (2016), pp.42-59.

DEA SOFTWARE: MaxDEA, <http://maxdea.com/MaxDEA.htm>

DEMSETZ, H., “The structure of ownership and the theory of the firm,” *Journal of Law and Economics*, 26 (2), (1983), 375-390 ss.

ELLINGSEN, T., "Efficiency wages and x inefficiencies," *Scandinavian Journal of Economics*, 99 (4), (1997), 581-596. ss.

FARRELL MARSHALL J., "The Measurement of Productivity Efficiency," *Journal of the Royal Statistics Society, Vol.120*, (1957).

FARRELL, M. J., AND M. FIELDHOUSE, "Estimating efficient production under increasing returns to scale," *Journal of the Royal Statistical Society, Vol.125, Series A*, (1962), pp.252-267.

FERRIER, G.D., AND C.A.K. LOVELL, "Measuring cost efficiency in banking: econometric and linear programming evidence," *Journal of Econometrics, Vol.46*, (1990), pp.229-245.

FRANTZ, R., TOMER, J., LEIBENSTEIN, H., "Worker motivation and x-efficiency theory: A comment," *Journal of Economic Issues, 16 (3)*, (1982), 864-873. ss.

GÖKGÖZ, F., "Veri Zarflama Analizi and Finans Alanına Uygulanması," *Ankara Üniversitesi Siyasal Bilgiler Fakültesi, No: 597*, (2009).

HART, O., "Incomplete Contracts and the theory of the firm," *Journal of Law, Economics, and Organization, 4 (1)*, (1988), 119-139. ss.

HOLID, D., LEWIS, H.F., "Resolving the deposit dilemma: a new D.E.A. bank efficiency model," *Journal of Banking and Finance 35 (1)*, (2011), 2801–2810.

IAGO COTRIM HENRIQUES, VINICIUS AMORIM SOBREIROA, HERBERT KIMURAA, ENZO BARBERIO MARIANO, "Efficiency in the Brazilian banking system using data envelopment analysis," *Future Business Journal 4*, (2018), 157–178

JENSEN, M.C. AND MECKLING, W.H., "Theory of the Firm: Managerial Behaviour, Agency Costs, and Ownership Structure," *Springer, Dordrecht*, (1979).

KILIAN HUBER, "Are Bigger Banks Better? Firm-Level Evidence from Germany," *CESifo Working Paper Series 8746*, (2020).

KOOPMANS, T. C., "Three Essays on the State of Economic Science," *McGraw-Hill, New York*, (1957).

LEACH, J., "A course in public economics," *London: Cambridge University Press*, (2004).

LEIBENSTEIN, H., "Allocative efficiency versus x-efficiency," *American Economic Review, 56 (3)*, (1966), 392-415. ss.

LEIBENSTEIN, H., "Competition and x-efficiency: Reply," *The Journal of Political Economy, 81 (3)*, (1973), 765-777 ss.

LEIGH DRAKE MAXIMILIAN J. B. HALL, “Efficiency in Japanese banking: An empirical analysis,” *Journal of Banking & Finance* Volume 27, Issue 5, (2003), pages 891-917.

LEIGH DRAKE MAXIMILIAN J. B. HALL RICHARD SIMPER, “The impact of macroeconomic and regulatory factors on bank efficiency: A non-parametric analysis of Hong Kong’s banking system,” *Journal of Banking & Finance* Volume 30, Issue 5, (2006), pages 1443-1466

LÉOPOLD SIMAR, PAUL W. WILSON, “Estimation and inference in two-stage, semi-parametric models of production processes,” *Journal of Econometrics* Volume 136, Issue 1, (2007), pages 31-64.

M. E. DUARTE NEVES, M. D.O. C. GOUVEIA AND C. A. NEVES PROENÇA, “European Bank’s Performance and Efficiency,” *Journal of Risk and Financial Management*, (2020).

MARTIN, J., “X-inefficiency, managerial effort and protection,” *Economica*, 45, (1978), 273-286. ss.

MCKINLEY & BANAIAN, “Central Bank Operational Efficiency: Meaning and Measurement,” *Central Banking Publications*, (2005).

MOHAMED DIA, A. GOLMOHAMMADI, AND P. M. TAKOUDA, “Relative Efficiency of Canadian Banks: A Three-Stage Network Bootstrap D.E.A.,” *Journal of Risk and Financial Management*, (2020).

NEWBERY, D., STIGLITZ, J., “Wage rigidity, implicit contracts, unemployment, and economic efficiency,” *The Economic Journal*, 97 (386), (1987), 416-430. ss.

PEEL, D. A., “A note on x-inefficiency,” *The Quarterly Journal of Economics*, 88 (4), (1974), 687-688 ss.

PETER BOGETOFT, LARS OTTO, “Benchmarking with D.E.A., S.F.A., and R,” *International Series in Operations Research & Management Science*, (2011).

PHONG HOANG NGUYEN AND DUYEN THI BICH PHAM, “The cost-efficiency of Vietnamese banks – the difference between D.E.A. and S.F.A.,” *Journal of Economics and Development* Vol. 22 No. 2, (2020) pp. 209-227.

R. W. SHEPHARD, “Theory of Cost and Production Functions,” *The Economic Journal* Vol. 82, No. 327 (1972).

ROZEN, M., “Maximizing behaviour: Reconciling neoclassical and x-efficiency approaches,” *Journal of Economic Issues*, 19 (3), (1985), 661-689. ss.

- SAID JAOUADI & ILHEM ZORGUI, “Exploring Effectiveness and Efficiency of Banks in Switzerland,” *International Journal of Academic Research in Business and Social Sciences*, vol. 4(4), (2014) pages 313-325.
- SAN-JOSE, L., RETOLAZA, J.L., PRUÑONOSA, J.T., “Efficiency in Spanish banking: a multistakeholder approach analysis,” *Journal of International Financial Markets, Institutions & Money* 32, (2014) 240–255.
- SEIFORD, L.M., “Data envelopment analysis: the evaluation of state of the art (1978-1995),” *The Journal of Productivity Analysis*, Vol.7, (1996), pp.99-137.
- SEITZ, W.D., “The measurement of efficiency relative to a frontier production function,” *American Journal of Agricultural Economics*, Vol.52, (1970), pp.505-511.
- STENNEK, J.,” Competition increases x-efficiency: A limited liability mechanism,” *European Economic Review*, 44 (9), (2000), 1727-1744. ss.
- SUDIT, E.F., “Productivity measurement in industrial operations,” *European Journal of Operational Research*, Vol.85, (1995), pp.435-453.
- TODD, D., “The relative efficiency of small and large firms,” *Committee of Inquiry on Small Firms Research Report, No:18, HMSO*, (1971).
- VISCUSI, K., VERNON, J., HARRINGTON, J. “Economics of regulation and antitrust,” *London: The M.I.T. Press*, (2000).
- WILLIAMSON, O., “Transaction cost economics: The governance of contractual relations,” *Journal of Law and Economics*, 22 (2), (1979), 3-61. ss.
- C. MENARD, M. SHIRLEY (ed.), “Handbook of new institutional economics,” *Netherlands: Springer*, (2005).
- YOLALAN, R., İşletmeler Arası Görelî Etkinlik Ölçümü, *Millî Prodüktivite Merkezi Yayınları*, No: 483, (1993).

ACKNOWLEDGEMENT

First of all, I would like to express my gratitude to my supervisor, Professor Antonella Basso, for her continuous support to finish my thesis and her professionalism. I am genuinely grateful for her continued support throughout this process. During this time, she has never spared herself from helping me prepare my thesis and overcome other problems related to my graduation. Indeed, my professor has made a great effort in my work, and I would like to express my sincere thanks for all her help.

Moreover, I would like to thank Ca' Foscari University for the numerous opportunities that students are provided with. When I started to study at this university, I was impressed by the friendly and understanding approach of the professors and university staff. This university has added significant value to me and created great opportunities for my future career.

This thesis is dedicated to my parents, who made my studies possible, and to all my family believing in me and supporting me during tough times. During this process, my family trusted and helped me a lot. Their support always gave me strength and never made me feel alone.

Sincerely Namig Alasgarov