INVESTIGATING EUROSYSTEM CENTRAL BANKING EFFICIENCY: A DATA ENVELOPMENT ANALYSIS APPROACH

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Abstract
Very few studies investigated central banking efficiency. Although Data Envelopment Analysis is widely used to measure efficiency within the banking industry, it has surprisingly never been implemented in a central banking context. In our study, we employ a radial DEA model to measure Eurosystem central banking efficiency. The Eurosystem monetary scheme offers interesting properties that allow DEA to be implemented with minimum noise. Considering price stability as the core Eurosystem mission, our results point out that National Central Banks (NCBs) operate at an average Technical Efficiency of 58.37% which indicates a significant scope for improvement. In addition, we observe an important disparity between NCBs' efficiency scores. We find the efficient units to be the central banks of Spain, Finland, the Netherlands and Lithuania while the most inefficient units are the central banks of Malta and Greece with a technical efficiency of 19.76% and 14.20% respectively. Finally, analyzing the peer units' set, we've reached the conclusion that the central banks of Spain and Finland should be designated as the leading NCBs in the context of a central banking efficiency improvement's project.

Keywords: *Efficiency analysis, Data Envelopment Analysis, central banking.*

JEL codes *: H21, E58, F02*

Résumé
Très peu d'études ont examiné l'efficacité de la banque centrale. Bien que l'analyse d'enveloppement des données soit largement utilisée pour mesurer l'efficacité au sein du secteur bancaire, elle n'a étonnamment jamais été mise en œuvre dans un contexte de banque centrale. Dans notre étude, nous utilisons un modèle DEA radial pour mesurer l'efficacité des banques centrales de l'Eurosystème. Le schéma monétaire de l'Eurosystème offre des propriétés intéressantes qui permettent de mettre en œuvre le DEA avec un minimum de bruit. Considérant la stabilité des prix comme la mission principale de l'Eurosystème, nos résultats indiquent que les banques centrales nationales (BCN) fonctionnent avec une efficacité technique moyenne de 58,37%, ce qui indique une marge d'amélioration importante. De plus, nous observons une importante disparité entre les scores d'efficacité des BCN. Nous trouvons que les unités efficaces sont les banques centrales d'Espagne, de Finlande, des Pays-Bas et de Lituanie, tandis que les unités les plus inefficaces sont les banques centrales de Malte et de Grèce avec une efficacité technique de 19,76% et 14,20% respectivement. Enfin, en analysant l'ensemble des unités homologues, nous sommes parvenus à la conclusion que les banques centrales d'Espagne et de Finlande devraient être désignées comme les principales BCN dans le cadre d'un projet d'amélioration de l'efficacité de la banque centrale.

Mots-clés: *analyse d'efficacité, analyse d'enveloppement de données, banque centrale.*
JEL codes *: H21, E58, F02*

1-.Introduction

While many researches have investigated banking efficiency, very few studies have focused on Central banks (CBs). It is widely admitted that CBs play a critical role in the economy and perhaps the efficiency gains that could be established may seem accessory in comparison to their effectiveness in achieving their core and secondary objectives, nonetheless there are arguments in favor of a central bank efficiency's improvement (McKinley and Banaian, 2005). Firstly, it should not be assumed that there is a trade-off between efficiency and effectiveness as a central bank may enhance its effectiveness by improving its efficiency. Secondly, most CBs are state-owned and therefore improving their efficiency leads to an increased flow of funds toward the government. Finally, due to the accountability characteristics of a central bank vis-à-vis to some oversight organs, perceived inefficiency could undermine its independence (McKinley and Banaian, 2005).

A significant factor that inhibits the implementation of an efficiency analysis within CBs lies on the complex mechanisms undertaken by this kind of institution in order to achieve its targets. In addition, the plurality of objectives assigned to CBs are generally heterogeneous from an economy to another which makes the comparison a complex task (Mester, 2003). This issue is accentuated by the fact that there are generally no peers for a central bank within a single country. Finally, as a legislative monopoly is granted in favor of CBs, they are totally free from any form of competitive pressure. In consequence, the incentives to perform efficiently is mitigated. There are two sources of inefficiency within a central bank, legislative and managerial (McKinley and Banaian, 2005). The former occurs when a central bank is assigned conflicting objectives undermining its faculty to focus on its core missions. The latter is observed when the objectives are well designed but pursued in a wasteful fashion. In our research, we focus on managerial inefficiency.

European countries that adopted the single currency entrust the management of their monetary policy to the so-called European System of Central Banks (ESBC). The European Central Bank (ECB) and the National Central Banks (NCBs) of Member States that have adopted the Euro exercise the main functions of the ESCB under the name "Eurosystem" (Scheller, 2004). The ECB has a full autonomy in conducting its monetary policy and is financially independent, moreover it is forbidden for the ECB to grant credits or other financing to governments and public authorities in the euro area (Fandl, 2018).Price stability has been assigned as the core objective of the Eurosystem. Quantitatively, the ESBC seeks to maintain the euro area inflation rate at levels below, but close to 2% over the medium term. The euro area inflation rate is based on a year-on-year evolution in the Harmonized Index of Consumer Prices (HICP), which is published on a monthly basis by Eurostat, the statistical agency of the European Union (Fandl, 2018).

In this study, we'll measure Eurosystem central banking efficiency using a widely applied technique called Data Envelopment Analysis (DEA). Implementing the DEA methodology at the Eurozone central banking level offers several advantages. First of all, NCBs rely on the same accounting principle in elaborating their financial reports which make variables comparison straightforward. Secondly, as they have the same currency, there is no need for any conversion. Thirdly, it's the monetary system with the most numerous central banks (19 NCBs). Finally, given the fact that there is a free movement of goods, services and capital in

conjunction with a harmonized banking legislation, it is relatively safe to consider the Eurosystem central banking environment as homogeneous. This is supported by the second part of the Article 105 of the Maastricht Treaty that states:
"The ESCB shall act in accordance with the principle of an open market economy with free competition, favoring an efficient allocation of resources (…)."

Following the aforementioned arguments, the DEA implementation is well adapted as the measurement errors and fluctuations are minimized. It is worth noting that to the best of our knowledge, there is no prior study that assessed central banks' relative efficiency using DEA. Off course, the DEA should be considered as a complementary measure and associated with other techniques (e.g., the Stochastic Frontier Analysis) and the results obtained should be interpreted with caution and confirmed with a substantial robustness analysis. In this research, we aim to demonstrate that the application of the DEA methodology within the central banking industry is possible and accessible to researchers and practitioners even though they may be not familiar at first glance with the DEA technique.

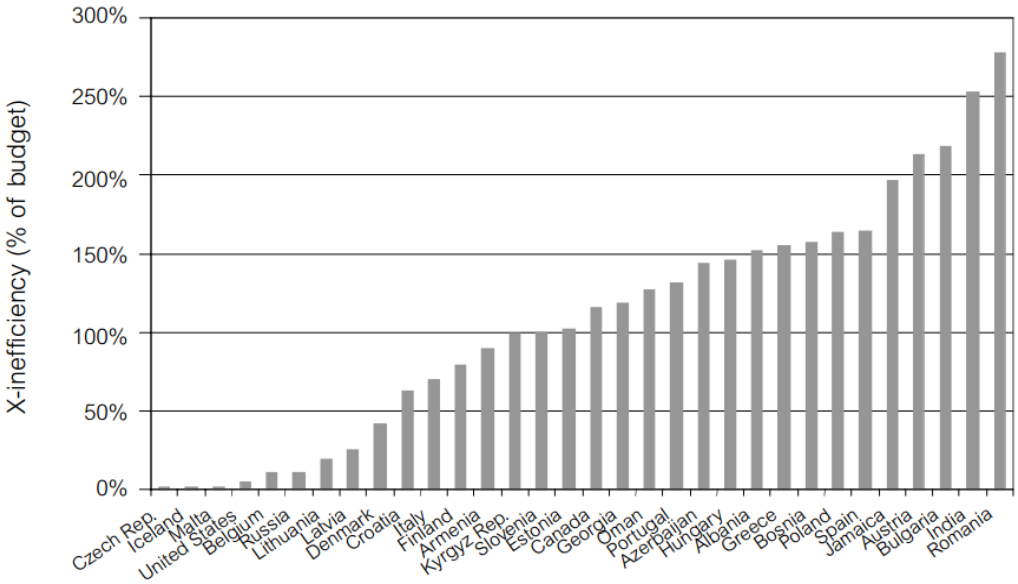
1-1-.Literature review

Researches onCBs' efficiency measurement are extremely scarce. According to Mester (2003), this is due to the complexity and uniqueness of many central banking activities. For this reason, some studied focused only on a specific type of operations within a predefined central banking system. As an example, Bauer and Hancock (1993) investigated the efficiency and productivity growth of check processing operations at 47 Federal Reserve offices over the period 1979-1990. For robustness purposes, they employed various econometric and linear programming models. They stated that check processing activities had no significant technological progress over the sample period. Further, they found that the measured cost inefficiency dominated scale inefficiency. In the same context, Bauer and Ferrier (1996) examined the Federal Reserve's costs of processing three payment services: checks, automated clearinghouse transfers and wire transfers of funds, over the period 1990 and 1994. To that aim, they relied on a stochastic parametric model. They found a significant dispersion in the operating performances of the various sites of processes for all three payment services. In addition, they pointed out that electronic services (automated clearinghouse transfers and wire transfers of funds) have both experienced rapid technological change due to the sharp decline in computer and equipment's prices while check-processing costs had raised during the same period. Furthermore, Bohn et al. (2001)considered another type of central banking activity, namely currency distribution. The authors estimated scale and cost efficiency for 37 Federal Reserve currency processing and handling facilities over the period the period 1991-1996using a translog and a hybrid-translog cost function. They observed that the facilities operated at an average of 80% of efficiency which was comparable to the cost-efficiency's estimate reported from private-sector financial institutions.

Although the authors provided relevant insights on some CBs' core activities, they've only focused on the efficiency at an internal level. In order to construct their frontier, they compared several units belonging to the same central bank which is the Federal Reserve. Our researcher takes the analysis at the institutional level, considering the institutional entity of a central bank as an independent unit. Furthermore, we're interested in the ability of central banks to accomplish their strategic mission (price stability) in an efficient manner, rather than considering a specific secondary activity like currency distribution and payments processing. To the best of our knowledge, there is only one study that attempted to measure efficiency at an institutional central banking level. Indeed, McKinley and Banaian (2005) were the first to measure empirically CBs' operational efficiency. They used data on 32 central banks for the year 2001. Country's selection was simply based on data availability. In order to conduct their analyses, they've chosen to implement a stochastic parametric model instead of a DEA model due to the strong disparity between the considered economics. The results associated with their analysis are reported in figure 1:

Although McKinley and Banaian (2005) provided useful insights and were the first to measure central banking efficiency, several caveats apply to their results. First of all, they compared central banks with different mandates, thus having different objectives and strategies. Secondly, they assumed the cost of capital for central banks to be the same. This is a strong assumption that is not verified in practice. Finally, the inputs introduced in the analysis were quantified in different currencies, as such the results might be biased by the exchange rate used to convert the input variables to the same currency. Our study tries to correct for those bias by analyzing the most homogenous monetary system in the world which is the euro system.

Fig. 1. Ranking of central bank inefficiency estimates



Source: McKinley and Banaian (2005), p.60.

2-.Methodology

DEA is a non-parametric linear programming technique that measures the relative efficiency of a set of homogeneous Decision-Making Units (DMUs). It was introduced for the first time by Charnes et al., (1978). Unlike regression, DEA optimizes on each individual DMU with an objective of calculating a discrete piecewise frontier determined by the set of Pareto-efficient DMUs (Charnes et al., 1994). DEA doesn't assume any production technology, it measures efficiency by estimating a production technology from the observed historical or cross-sectional data on reel production activities (Bogetoft and Otto, 2010). DEA measures the efficiency of a DMU in comparison to other DMUs within an organization or in a similar industry that's why the efficiency measure obtained is called a relative efficiency (Vafaee Najar et al., 2018). In addition, DEA provides a set of peer-units against which the inefficient DMUs can learn to improve. Therefore, it has the ability to establish coherent improvement targets for each inefficient Decision-Making Unit. Another advantage of DEA is that it allows to study organizations with multidimensional processes that includes several inputs against several outputs. While DEA has never been implemented to measure central banking efficiency, it is the most widely used operational research method to assess banking efficiency (Fethi and Pasiouras, 2010). Indeed, Paradi and Zhu (2013) counted 257 DEA applications in the banking industry between 1985 and 2011.

2-1-.DEA formulation

2.1.1-. The CCR Model

The CCR model initially developed by Charnes et al. (1978) is a model that assumes a Constant Returns to Scale (CRS) production technology. In other words, the operating size of the DMUs doesn't have an impact on their efficiency. It is one of the most widely used DEA models in the literature. It considers the i-th DMU and seeks as much as possible to radially contract its inputs (in the case of an input-oriented model) or radially expand its outputs (output-oriented model) while still remaining within the feasible production set. Suppose we have m input variables with a marginal weights vector$v_i (i = 1, \dots, m)$, s output variables with a marginal weights vector u_r $(r = 1, \dots, s)$, and n DMUs, the envelopment form of the input-oriented model is as follow:

$min_{\theta,\lambda}\theta$ (1)

Subject to
$$\theta x_o - X\lambda \geq 0$$
$$Y\lambda \geq y_o$$
$$\lambda \geq 0$$

where x_o and y_o the column vectors of inputs and outputs respectively for DMU_o. X and Y are the matrices of input and output respectively for all DMUs. λ is the column vector if intensity variables denoting linear combinations of DMUs, and the objective function θ is a radial contraction factor that can be applied to DMU_o's inputs. We measure the efficiency of each DMU once, thus we need n optimizations. The optimal value of θ, denoted θ^* is the efficiency score of the DMU in question. If θ^* is equal to 1, then the DMU_o is evaluated as fully efficient.

2.1.2-. The BCC Model

Banker et al. (1984) developed a radial DEA model where the production technology exhibits Variable Returns to Scale (VRS). It fits situations where the operating scale of an entity plays an important role in its performance. They introduced a new constraint ($e_n\lambda = 1$) in the CCR model that separated scale efficiency from technical efficiency. The envelopment form of the input-oriented version of the model is given as follow:

$$min_{\theta_B,\lambda}\theta_B \quad (2)$$

Subject to
$$\theta_B x_o - X\lambda \geq 0$$
$$Y\lambda \geq y_o$$
$$e_n\lambda = 1$$
$$\lambda \geq 0$$

The $e_n\lambda = 1$ constraint ensures that a DMU is only compared against firms of a similar size.

2-2-.Central Banks' Input and Output Factors Determination

In order to conduct an efficiency analysis on any organizational unit, a cautious selection of input and output variables must be undertaken. Input and output factors need to be selected according to the organization's core strategy and objectives. This is crucial in order to get a reliable, relevant and interpretable result.

Due to the limited number of DMUs in our analysis and in order to preserve DEA's discriminatory power, we decided to incorporate three variables. Two inputs and one output. The input factors are represented by:

- Fixed Assets to GDP,
- Salary Expenses to GDP.

The inputs data were extracted from NCBs income statement and balance sheet corresponding to the 2017 year. We believe that these inputs are the most resource consuming within a central bank. In order to account for countries' economic size, our inputs are adjusted to the respective 2017 GDP at market prices. GDP information were obtained from the Eurostat database.

Determining NCBs outputs was a challenging task due to the diversity of objectives assigned to this kind of institution, nonetheless we focused on NCBs' central mission. As mentioned above and according to the Article 105(1) of the Maastricht Treaty, the primary objective of the Eurosystem is to maintain price stability. Indeed, it is clearly stated that:

"The primary objective of the ESCB shall be to maintain price stability. Without prejudice to the objective of price stability, the ESCB shall support the general economic policies in the Community with a view to contributing to the achievement of the objectives of the Community (…)."

Consequently, price stability is a factor that each central bank should seek to maximize given its limited amount of inputs. To describe our output in a quantitative dimension, we rely on the Heritage Foundation index on monetary freedom. This index has been used as an output factor on a previous study on central banking efficiency using Stochastic Frontier Analysis, conducted by McKinley and Banaian (2005). The index of monetary freedom is part of an overall database entitled Index of Economic Freedom which encompasses information that focuses on key aspects of the economic environment over which government typically exercise policy control. The index of Economic Freedom is published annually by the Heritage Foundation.

The monetary freedom index combines a measure of price stability with an assessment of price controls. It is based on two sub-factors:

- The average weighted inflation rate for the most recent three years,
- Price controls.

The average weighted inflation rate for the most recent three years serves as the primary input into an equation that generates the base for monetary freedom. The extent of price controls is then assessed as a penalty deduction of up to 20 points from the base score. The two equations used to convert inflation rates into the final monetary freedom score are:

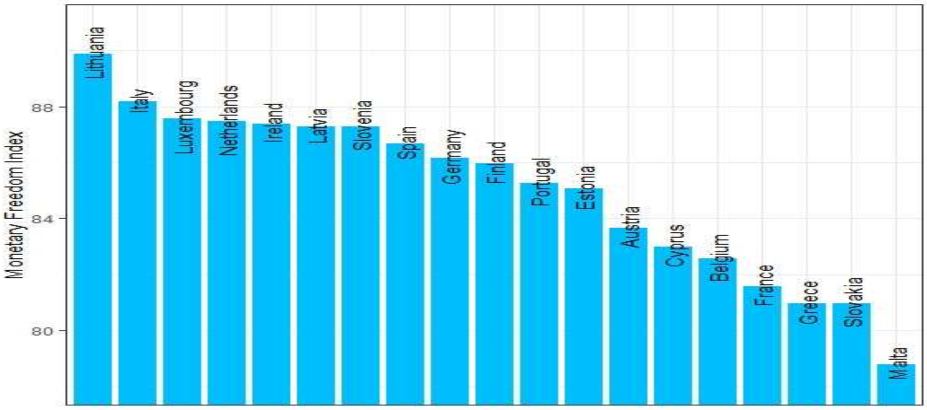
$$WeightedAvg.Inflation_i = \theta_1 Inflation_{it} + \theta_2 Inflation_{it-1} + \theta_3 Inflation_{it-2} \quad (3)$$

$$MonetaryFreedom_i = 100 - \alpha\sqrt{WeightedAvg.Inflation_i} - PCpenalty_i \quad (4)$$

Where θ_1 through θ_3 represents three numbers that sum to one and are exponentially smaller in sequence. $Inflation_{it}$ is the absolute value of the annual inflation rate in country i during year t as measured by the Consumer Price Index (CPI). The value α represents a coefficient that stabilizes the variance of the score. Finally, the price control (PC) penalty is an assigned value of 0-20 points based on the extent of price controls. The convex (square root) functional form was chosen to create separation among countries with low inflation rates.

The index of monetary freedom is pertinent because it encompasses several periods in order to measure a central bank capacity to perform its monetary mandate. Considering three periods gives a more accurate vision of the short-term performance of a central bank in achieving price stability. Figure 2 shows the Monetary Freedom Index value for each Eurozone country in 2017.

Fig.1. Monetary Freedom Index for Eurozone countries



Since our input variables are presented in the form of ratios to account for economies' size, it is de facto that we are assuming Constant Return to Scale. That is, we assume that the economy's size of the Euro zone members doesn't affect their efficiency according to their price stability mandate. As a consequence, a CRS model should be implemented however the use of this model in this situation leads to incorrect results and the BCC formulation is more suitable (Hollingsworth and Smith, 2003). We refer our readers to the article written by

Hollingsworth and Smith (2003) for a detailed technical argumentation on why the CBB model needs to be implemented when some factors are expressed in ratios. Concerning the orientation of our model and given the complexity of the monetary mechanisms, we believe NCBs have a better control over their inputs, as a consequence we decided to implement an input-oriented DEA model. We rely on the work of Paradi et al. (2017) to describe the DEA BCC mathematical formulations and we use the Benchmarking package developed by Bogetoft and Otto (2010) in the R software to run our calculations.

3-.Results and discussion

Table 1 and Figure 3 exhibit the NCBs' efficiency scores. We observe that the average Technical Efficiency (TE) equals 58.37%. Consequently, NCBs benefit from a tremendous scope for efficiency improvement. Moreover, we see that half of the NCBs have a TE inferior to 51.27% denoting a strong heterogeneity within the Eurosystem. Among 19 NCBs 4 are efficient: The central banks of Spain, Finland, the Netherlands and Lithuania. It is interesting to observe that the central bank of Lithuania is efficient even though the country was the last to adopt the euro currency in on 1st January 2015. On the other hand, the most inefficient units are the central banks of Malta and Greece with a technical efficiency of 19.76% and 14.20% respectively. They demonstrate a weak ability in exploiting their resources in order to achieve their price stability target.

Figure 3: EurozoneNational Central Banks' TechnicalEfficiency

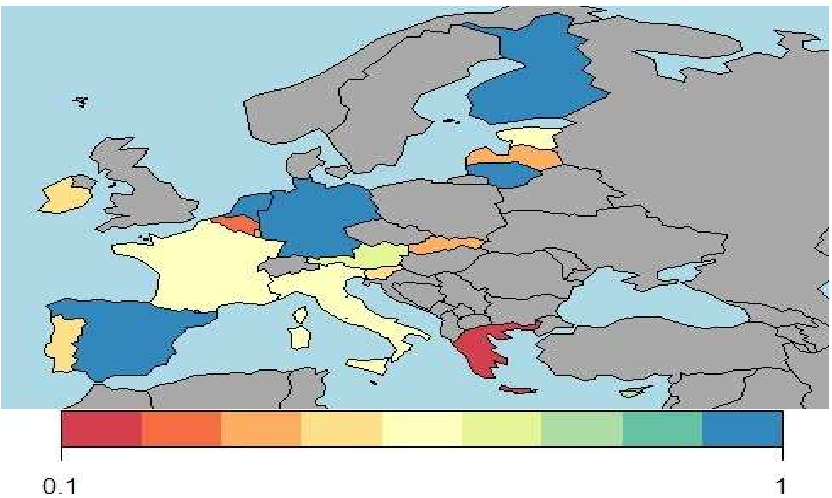


Table 1. EurozoneNational Central Banks' Technical Efficiency

NCBS	TE	NCBS	TE
SPAIN	**1.0000**	SLOVENIA	0.4603
FINLAND	**1.0000**	IRELAND	0.4538
NETHERLANDS	**1.0000**	PORTUGAL	0.4056
LITHUANIA	**1.0000**	SLOVAKIA	0.3906
GERMANY	0.9966	LUXEMBOURG	0.3534
CYPRUS	0.7885	LATVIA	0.3025
AUSTRIA	0.6624	BELGIUM	0.2803
ITALY	0.5876	MALTA	0.1976
ESTONIA	0.5582	GREECE	0.1420
FRANCE	0.5128		
Mean	**0.5837**		
Median	**0.5127**		

One of the main benefits of DEA is that it identifies explicit real peer-units for every evaluated DMU (Bogetoft and Otto, 2010). The λ values denote the relative contribution of the efficient peers in measuring inefficient DMUs' score. Hence, it is straightforward to determine the suitable units that an inefficient central bank could emulate to improve its efficiency. This may be useful for the European Central Bank in order to allocate audit resources in an intuitive way. In this context and according to Table 2, the central banks of Spain, Finland, the Netherlands and Lithuania compose our reference set, nevertheless the central banks of Spain and Finland contribute the most in measuring inefficient DMUs'

Technical efficiency. Thus, they may be designated as the leading central banks when an efficiency improvement project is initiated within the Euro area.

Table 2. Reference set and λ values for the inefficient NCBs

NCBS	NETHERLANDS	**SPAIN**	**FINLAND**	LITHUANIA
AUSTRIA	0.0000	**1.0000**	**0.0000**	0.0000
BELGIUM	0.0000	**0.9367**	**0.0633**	0.0000
CYPRUS	0.0000	**1.0000**	**0.0000**	0.0000
ESTONIA	0.0000	**0.5014**	**0.4986**	0.0000
FRANCE	0.0000	**0.4336**	**0.5664**	0.0000
GERMANY	0.0000	**1.0000**	**0.0000**	0.0000
GREECE	0.0000	**0.3686**	**0.6314**	0.0000
IRELAND	0.3835	**0.4936**	**0.0000**	0.1229
ITALY	0.0000	**0.5313**	**0.0000**	0.4687
LATVIA	0.0000	**0.8125**	**0.0000**	0.1875
LUXEMBOURG	0.1863	**0.5790**	**0.0000**	0.2347
MALTA	0.0000	**0.0000**	**1.0000**	0.0000
PORTUGAL	0.0000	**1.0000**	**0.0000**	0.0000
SLOVAKIA	0.0000	**0.0000**	**1.0000**	0.0000
SLOVENIA	0.0000	**0.8125**	**0.0000**	0.1875

4-.Conclusion

Since our input variables were represented in ratios, we've assumed implicitlya Constant Returns to Scale technology. Nonetheless, in order to measure NCBs' relative efficiency, we employed the BCC model formulation as suggested by Hollingsworth and Smith (2003). We find that Eurozone National Central Banks operate at an average Technical Efficiency of 58.37% with a median equal to 51.25% indicating an important heterogeneity within NCBs' efficiency. Moreover, from 19 NCBs the central banks of Spain, Finland, the Netherlands and Lithuania are efficient. On the other hand, the most inefficient NCBs are the central banks of Malta and Greece. Finally, analyzing our reference set, we observe that the central banks of Spain and Finland contribute the most in measuring inefficient NBCs' score. As a consequence, they may be assigned the leading role in the context of an efficiency improvement project. In terms of policy implications, the ECB could implement the DEA methodology in complementarity with other analysis in order to monitor the efficiency of NCBs across different periods (quarterly, semesterly or yearly). Further, NCBs with low efficiency can emulate the most efficient ones. In practice, this can be done through bilateral partnerships which aim to spread the best practices among the inefficient NCBs. Finally, the European Central Bank may exploit the DEA's results for reallocating central banks' activities and resources.

5-.References

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science 30, 1078-1092.

Bauer, P.W., Ferrier, **G.D.**, 1996. Scale Economies, Cost Efficiencies, and Technological Change in Federal Reserve Payments Processing. Journal of Money, Credit and Banking 28, 1004–1039. https://doi.org/10.2307/2077938

Bauer, P.W., Hancock, D., 1993. The efficiency of the Federal Reserve in providing check processing services. Journal of Banking & Finance, Special Issue on The Efficiency of Financial Institutions 17, 287–311. https://doi.org/10.1016/0378-4266(93)90033-A

Bogetoft, P., Otto, L., 2010. Benchmarking with Dea, Sfa, and R. volume 157. Springer Science & Business Media.

Bohn, J., Hancock, D., Bauer, P., 2001. Estimates of scale and cost efficiency for Federal Reserve currency operations. Economic Review, Federal Reserve Bank of Cleveland 37, 2–26.

Charnes, A., Cooper, W.W., Lewin, A.Y., Seiford, L.M. (Eds.), 1994. Data Envelopment Analysis: Theory, Methodology, and Applications. Springer Netherlands.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision-making units. European Journal of Operational Research 2, 429-444.

Fethi, M.D., Pasiouras, F., 2010. Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. European Journal of Operational Research 204, 189-198

Hollingsworth, B., Smith, P., 2003. Use of ratios in data envelopment analysis. Applied Economics Letters 10, 733-735.

McKinley, V., Banaian, K., 2005. Central bank operational efficiency: meaning and measurement.

Mester, L.J., 2003. Applying efficiency measurement techniques to central banks. University of Pennsylvania-The Wharton School.

Paradi, J.C., Sherman, H.D., Tam, F.K., 2017. Data Envelopment Analysis in the Financial Services Industry: A Guide for Practitioners and Analysts Working in Operations Research Using DEA. volume 266. Springer.

VafaeeNajar, A., Pooya, A., Alizadeh Zoeram, A., Emrouznejad, A., 2018. Assessing the Relative Performance of Nurses Using Data Envelopment Analysis Matrix (DEAM). J Med Syst 42, 125. https://doi.org/10.1007/s10916-018-0974-x