Revenue efficiency: a distributional analysis in the European banking

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Abstract: This paper uses data envelopment analysis (DEA) to compare efficiency estimated according to the traditional revenue model presented by Farrell (1957) and a new revenue model presented by Tone (2002). First, we estimated the revenue efficiency of 114 European banks during the period from 2010 to 2018. The results showed that the average traditional revenue efficiency ranged from 35.74% to 38.85%, and average new revenue efficiency ranged from 37.82% to 54.99%. The results of the analysis showed that banks located in Northern Europe and large banks seem to be most efficient. After the estimation of efficiencies, the nonparametric test for equality of densities was used to test whether two given distributions, estimated nonparametrically via kernel smoothing, differ statistically in terms of the size and geo-scheme for Europe. Based on the results of distribution hypothesis tests, we could confirm our research questions that depended on size, location and applied methodology.

Keywords: commercial banks; DEA; data envelopment analysis; distributional analysis; Europe; Li test; new revenue model; non-parametric methods; software R; traditional revenue model.

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1 Introduction

According to Cooper et al. (2007), technology and revenues are the wheels that drive modern businesses. Some businesses have an advantage in terms of technology and others in revenues. Therefore, the management is eager to see how and to what extent their resources are being used effectively, compared to other similar businesses in the same or similar area. In the literature, there are two main methods to measure revenue efficiency: the parametric approach and the non-parametric approach. These two approaches differ primarily in the underlying assumptions applied in estimating revenue efficient frontiers. The most commonly used parametric approach is the stochastic frontier approach (SFA) as it allows to separate the effect of statistical noise from the effect of inefficiency, leading to a stochastic frontier. This approach, however, requires a specific functional form, which assumes the shape of the revenue efficiency frontier and assumes a specific probability distribution for the level of efficiency. Besides, if the assumptions are incorrectly specified, the measured revenue efficiency will contain errors. Non-parametric approach, commonly known as data envelopment analysis (DEA), avoids this error specification, as a priori assumptions about the analytical form of the revenue function or an expected probability distribution in terms of efficiency are not required. One major disadvantage is that it does not allow for random errors (e.g., errors in measurement, good or bad luck) in the optimisation problem and any deviations from the revenue efficiency frontier are measured as inefficiency.

When measuring efficiency based on the DEA method, there are two different situations: one with common unit prices of outputs for all Decision-Making Units (DMUs) and the other with different prices of outputs from DMU to DMU. Revenue efficiency evaluates the ability to produce maximum possible outputs at given inputs, at maximal revenues. The concept of revenue efficiency was first introduced by Farrell (1957) and then developed by Färe et al. (1985) by using linear programming technologies. In this model, they assumed that output prices are the same across all DMUs. However, the common price and revenue assumption is not always valid in real business, and it has been shown that efficiency measures based on this assumption can be misleading. So we decided to introduce a new revenue efficiency model introduced by Tone (2002) and compare the results obtained with the traditional and new revenue model. The aim is to present the advantages and disadvantages of both methods and to introduce their use for efficiency evaluation in the banking area. We want to present the usage of these methods in efficiency evaluation in software RStudio, namely application of package 'Benchmarking'.

Commercial banks represent the largest segment of the European financial system. In the last years, because of their importance, many regulatory and supervisory norms were taking into account. However, banks with different size or in different countries face different constraints that derive from the policies of regulatory and policies of the government. Used inputs and produced outputs, cost and revenue structures, and skills of management vary widely between banks located in Northern and Western Europe and banks located in Eastern Europe, and also between large and smaller one. There is, therefore, necessary, to study efficiency in order to differentiate the efficient one from non-efficient ones and to find out which conditions are the most prerequisite to becoming efficient.

This study aims to examine the revenue efficiency of the European banks using the DEA and try to answer the research question whether the efficiency differs across banks with different size, and banks from different European regions. The efficiency is evaluated in a sample of 114 banks during the period from 2010 to 2018 based on the database Datastream published by Thomson Reuters. The database includes data for banks which are traded on the stock exchange. The DEA technique is applied due to its flexibility to include multiple inputs and multiple outputs to measure relative efficiency within the dataset under the defined criteria. In the next step, the estimated efficiencies are tested for equality of densities of two given distributions via the test prepared by Li et al. (2009). The advantage and justification for the use of this methodology in the process of significant differences identification is that both DEA and test for equality of densities are nonparametric methods. This study contributes to the existing literature by providing new empirical evidence of how this method could be applied to examine the statistical differences in equality of efficiencies in terms of the size and geographical region. Therefore, one of the benefits of this paper is filling the current gap in the scientific literature, as this type of analysis is missing in the literature concerning the banking sectors in the EU countries.

To fulfil the aim of the paper, the structure of the paper is as follow. The review of the relevant literature is described in Section 2. Section 3 describes the methodology. Next, Section 4 presents the empirical analysis and results. In Section 5, we conclude the paper.

2 Literature review

The literature on bank efficiency has expanded during the last years. The earliest techniques usually measured revenue efficiency through financial ratios, examined financial statements of individual banks. More recently, the researchers started to prefer parametric and nonparametric methods to evaluate the revenue efficiency of commercial banks within the national economy, or for international evaluation.

As mentioned by Dong et al. (2014), since both parametric and non-parametric approaches have their advantages and limitations and since the actual level of revenue efficiency is unknown, the choice of an appropriate efficiency estimation approach has been quite controversial. In the banking area, some researches, for example, Rossi et al. (2005), Fitzpatrick and McQuinn (2008), Matousek (2008), Papadopoulos (2010), Olson and Zoubi (2011), Rouissi (2012), Ghroubi and Abaoub (2016) prefer parametric method, while some researches like Havranek and Irsova (2013), Pancurova and Lyócsa (2013), Mozaffari et al. (2014), Prior Jiménez et al. (2016), Gavurova et al. (2017), Palečková

(2018), Pavković et al. (2018), or Phang and Raweewan (2018), mainly used the non-parametric approach. We can also find several studies, for example, Delis et al. (2009), Irsova (2009), Tan (2016), or Ruinan (2019) comparing the results of revenue efficiency estimated by both methods simultaneously. Most of these studies apply the traditional revenue efficiency frontier. However, in the study of Pancurova and Lyócsa (2013), we can also find the application of a new revenue efficiency function.

Irsova (2009) provided empirical insight into the efficiency estimation methods in the banking area. She used two methods, SFA and traditional DEA to evaluate cost and revenue efficiency in the US and transition countries between the years 1995 and 2006. The results pointed to the fact that the efficiency score was highly depended on the methodological design.

Havranek and Irsova (2013) analysed what drove bank cost and revenue efficiency in the transition countries of Central Europa and compare results with those for the US. They applied the traditional DEA model to evaluate efficiency for the period of 1995–2006, based on intermediation approach. Three measures of bank output were included in the estimation: total loans, other operating assets and deposits. Furthermore, they had three inputs: personnel expenses, fixed assets, and deposit and other funds. They found out that the largest banks were most revenue efficient. Also, foreign banks reported higher cost and revenue efficiency. The revenue efficiency was higher than cost efficiency, which signalised that banks were more successful in gaining profits on average.

Pancurova and Lyócsa (2013) estimated efficiencies and their determinants for a sample of eleven Central and Eastern European Countries over the 2005–2008 period. They estimated cost and revenue efficiency using new DEA models. Within the second stage, they tested the separability assumption and estimated determinants of efficiency by using a truncated regression model. They found out that the size and financial capitalisation of banks were positively associated with cost and revenue efficiency, while the loans-to-assets ratio was negatively associated with cost efficiency but positively associated with revenue efficiency. Moreover, foreign banks were more cost-efficient but less revenue efficient than domestic banks, suggesting different banking behaviour between domestic and foreign banks.

Prior Jiménez et al. (2016) focused on the Spanish banking sector for the 2005–2009 period. They applied traditional DEA method to evaluate cost and revenue efficiency of Spanish commercial banks, savings banks and credit unions during both the pre-crisis years (from 2005 to 2007) and crisis years (2008 and 2009). They applied Li et al. (2009) test to analyse differences between groups of banks according to the type of bank and crisis years. They found out that differences did not exist when comparing saving banks and credit unions. In contrast, commercial banks were more efficient than the other two bank types.

Tan (2016) evaluated 100 Chinese commercial banks (5 large-scale, 12 joint-stock, and 83 city commercial banks) over the period 2003–2013. The findings pointed to the fact that city commercial banks had the highest cost and revenue efficiency, followed by state-owned commercial banks, whereas the cost and revenue efficiency of joint-stock commercial banks was the lowest. They also found out that Chinese commercial banks had lower cost efficiencies if they were operated in a more competitive market.

Gavurova et al. (2017) examined the cost and revenue efficiency of banking sectors within the European Union countries over the period 2008–2015. They considered three inputs, namely, total deposits, the number of employees and fixed assets. On the output side, they considered two outputs: total loans and other earning assets, which refer to non-lending activities. The price of the first output was defined as the ratio of interest income to the value of loans – the price of the second output as the ratio of total non-interest income to other earning assets. After the estimation of efficiencies, they tested if there exist differences in term of size, European region and crisis years. They found out that the results differ in the specified group, so they concluded that the results of analysis depended on size, location and crisis period.

Phang and Raweewan (2018) examined the cost, revenue and profit efficiency of the Cambodian banking system over the period 2010–2013 by traditional DEA model. They considered total fixed assets, total employees and total funds as inputs, and total loans and total other earning assets as outputs. The prices on the output side were calculated as the ratio of total interest incomes to total loans, and the ratio of total operating incomes to total other earning assets. They found out that large banks were more cost, revenue and profit efficient than smaller counterparts. Moreover, foreign banks, on average, were more cost, revenue and profit efficient than domestic banks. Results suggested that the banking sector still had the potential for cost savings as well as revenue and profit increases.

Ruinan (2019) applied both SFA and traditional DEA to evaluate cost and profit efficiency of the largest banks in the US and Canada for the 2008–2017 period. As the input variables number of employees, fixed assets and total deposits were used, while as the output variables they used loan. The results regarding cost and profit efficiency confirmed the prior studies indicating a low correlation between these two measures. However, SFA and DEA produced very different and uncorrelated results, though DEA generated overall lower efficiencies. The findings suggested that methodology cross-checking, along with information regarding variables selection, are necessary before decision making.

3 Methodology

Data envelopment analysis (DEA) was first developed by Charnes et al. (1978) under the constant returns to scale assumption and provides a measure of technical efficiency. Following Farrell (1957), and Färe et al. (1985), a sequence of linear programs was applied to construct revenue efficiency frontiers, and from these, measures of traditional revenue efficiency were calculated.

Berger and Mester (1997) argue that revenue efficiency measures the change in a bank´s revenues adjusted for a random error, relative to the estimated revenues obtained from producing an output as efficient as the best practice bank. According to Tan (2016), revenue efficiency emphasises the fact that the banking operations aim to maximise revenues, and revenue efficiency is calculated by the ratio of actual revenues to maximise revenues. According to the Pancurova and Lyócsa (2013), to be revenue efficient, the DMU must be both technically efficient (adopting the best practice technology) and allocative efficient (selecting the optimal mix of outputs to maximise the revenues for a given input).

The traditional revenue efficiency model (TRE) assumes that the unit price of outputs is identical among DMUs. We define $\mathbf{y_o}$ as the $s\times 1$ vector of the o-th production unit´s s outputs $(r = 1,...,s)$, $\mathbf{x_o}$ is the $m\times 1$ vector of its m inputs $(i = 1,...,m)$, $\mathbf{Y}$ is the $s\times n$

matrix of outputs (n denotes the number of DMUs, $(j = 1,...,n)$), and $\mathbf{X}$ is the $m \times n$ matrix of inputs. Let us consider we have prices associated with outputs. Let $\mathbf{p} = (p_1,..., p_s)$ be the common unit output-price or unit-revenue vector. Then the revenue efficiency ρ_o of DMU_o is defined as the ratio between the actual revenues and maximal revenues:

$$\rho_o = \frac{py_o}{py_o^*} \tag{1}$$

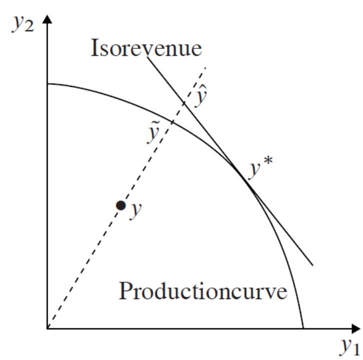
where y_o^* is an optimal solution of the constant returns to scale revenue maximisation DEA model defined in the following terms:

$$\text{Revenues } py^* = \max_{y,\lambda} py \tag{2}$$

$$\text{Subject to } x_o \geq X\lambda;\ y \leq Y\lambda;\ \lambda \geq 0 \tag{3}$$

The solution to this optimisation problem is known to be the point y^* where the isorevenue line is tangent to the production possibility frontier, as shown in Figure 1. This point represents the revenue maximising vector of output quantities for the evaluated production unit, given the vector of output prices $\mathbf{p_o}$ and input levels $\mathbf{x_o}$.

Figure 1 Revenues maximum



Source: Bogetoft and Otto (2010)

The production possibility frontier represents all possible combinations of outputs amount (y_1, y_2) that can be produced using the same amount of a single input. The point y is a point below the production possibility frontier representing the activity of a DMU which uses this same amount of input but produces a smaller amount of both outputs. To evaluate the performance of this production unit, we can use the traditional Farrell (1957) measure of radial efficiency. The result is th66e measure of technical efficiency which can be calculated as the ratio between the distance from 0 to $\tilde{y}$ and distance from 0 to y. If the information about the output prices is available, we can also define isorevenue line whose slope is given by the ratio of output prices. Isorevenue line shows all combinations of outputs which revenues have the same total amount. The relative distance of $\hat{y}$ and $\tilde{y}$ refers to allocative efficiency, which can bring maximal revenues but is connected with the loss of technical efficiency. To be fully revenue-efficient, a firm must demonstrate both full output technical efficiency (the point on the production possibility frontier) and full output allocative efficiency (the point on the isorevenue line). It must use the best procedures to get the most out of its resources, and it must produce the right mix of services.

In traditional revenue efficiency DEA models, we assume that output prices are the same across all decision-making units. However, actual markets do not necessarily function under perfect competition, and unit output prices might not be identical across all DMUs. Thus, as pointed out by Tone (2002), the traditional DEA revenue efficiency model does not take account of the fact that revenues can be increased by increasing the output factor prices. For example, if two production units have the same inputs and outputs while the unit output prices for one DMU are twice those of the other DMU, then the total revenues of the DMU with the higher unit output prices will be greater than those of the DMU with the lower unit output prices. However, under the traditional DEA model, the revenue function is homogeneous of degree one in output prices, and the scaling factor cancels out in the revenue efficiency ratio, and thus, the two DMU will be assigned the same measure of revenue efficiency irrespective of the fact that they have significantly different output prices. It represents a severe drawback for assessing relative efficiency levels under the traditional DEA model an is caused by the peculiar structure of the DEA model which exclusively focuses on the technical efficiency of two DMU and cannot take account of variations in unit output prices between the DMUs. Therefore, in order to avoid this shortcoming, Tone (2002) proposed a new scheme for evaluating revenue efficiency under which the production technology is homogeneous of degree one in the total revenues as distinct from being homogeneous of degree one in the output prices under the traditional DEA model. As mentioned by Dong et al. (2014), it means that under the new DEA model DMUs with different output prices will return different measures of revenue efficiency.

The new revenue efficiency model (NRE) is based on the definition of another revenue-based production possibility set P_R as:

$$P_R = \left\{ \left(x, \bar{y}\right) \middle| x \geq X\lambda, \bar{y} \leq \bar{Y}\lambda, \lambda \geq 0 \right\} \tag{4}$$

where $\bar{Y} = \left(\bar{y}_1, ..., \bar{y}_n\right)$ with $\bar{y}_j = \left(p_{1j}y_{1j}, ..., p_{sj}y_{sj}\right)$ where $(j = 1, ..., n)$. Here we assume that the matrices Y and P are non-negative, and elements of $\bar{y}_{rj} = \left(p_{rj}y_{rj}\right)\left(\forall\left(r, j\right)\right)$, where $(r = 1, ..., s)$ and $(j = 1, ..., n)$, are denominated in homogeneous units in monetary terms (e.g., euro). According to Cooper et al. (2007), new revenue efficiency $\bar{\rho}_o$ is defined:

$$\bar{\rho}_o = \frac{e\bar{y}_o}{e\bar{y}_o^*} \tag{5}$$

where $e \in R^m$ is a row vector with elements being equal to 1, and $\bar{y}_o^*$ is the optimal solution for the linear programs given below:

$$\text{New Revenues} \quad e\bar{y}_o^* = \max_{\bar{y}, \lambda} e\bar{y} \tag{6}$$

$$\text{Subject to} \quad x_o \geq X\lambda\,;\ \bar{y} \leq \bar{Y}\lambda\,;\ \lambda \geq 0 \tag{7}$$

In the new revenue efficiency model, the optimal output mix $\overline{y}_o^*$ that uses the input x_o can be found independently of the DMU′s current unit price p_o, whereas in the traditional revenue efficiency model keeping the unit revenue of DMU *j* fixed at p_o we search for optimal output mix y^* for using input x_o. These are fundamental differences between the two models. Using traditional revenue efficiency model, we can fail to precisely the existence of other more profitable output mixes.

Having estimated revenue and new revenue efficiency, we will test distributions of efficiencies for two sub-groups. We apply a nonparametric test for equality of densities prepared by Li et al. (2009) to test if there exist significant differences in terms of the bank size, and in terms of geo-scheme for Europe. Li et al., (2009) proposed a nonparametric test for equality of multivariate densities, comprised of continuous and categorical data. Let *X* and *Y* be multivariate vectors of a dimension $q+r$ where *q* denotes the number of variables from the first sample, and *r* denotes the number of variables from the second sample. According to Racine (2012) test statistic can be constructed based on the integrated squared density difference given by:

$$I=\int\left[f(x)-g(x)\right]^2\mathrm{d}x=\int\left[f(x)\mathrm{d}F(x)+g(x)dG(x)-f(x)dG(x)-g(x)dF(x)\right] \tag{8}$$

where $F(\cdot)$ and $G(\cdot)$ are the cumulative distribution functions for *X* and *Y*, respectively, and where $\int dx=\sum_{x^d\in s^d}\int dx^c$. Replacing the first occurrences of $f(\cdot)$ and $g(\cdot)$ by their leave-one-out kernel estimates, and replacing $F(\cdot)$ and $G(\cdot)$ by their empirical distribution functions, we obtain the following test statistics:

$$I_n=\frac{1}{n_1(n_1-1)}\sum_{i=1}^{n_1}\sum_{j\neq i}^{n_1}K_{\gamma,x_i,x_j}+\frac{1}{n_2(n_2-1)}\sum_{i=1}^{n_2}\sum_{j\neq i}^{n_2}K_{\gamma,y_i,y_j}-\frac{2}{n_1n_2}\sum_{i=1}^{n_1}\sum_{j=i}^{n_2}K_{\gamma,x_i,y_j} \tag{9}$$

Li et al. (2009) demonstrate that under the null of equality:

$$T_n=(n_1n_2h_1\ldots h_q)^{\frac{1}{2}}I_n/\sigma_n\to N(0,1)\text{ in distribution,} \tag{10}$$

Where:

$$\sigma_n^2=2\left(n_1n_2h_1\ldots h_q\right)\left[\frac{1}{n_1^2(n_1-1)^2}\sum_{i=1}^{n_1}\sum_{j\neq i}^{n_1}(K_{\gamma,x_i,x_j})^2+\frac{1}{n_2^2(n_2-1)^2}\sum_{i=1}^{n_2}\sum_{j\neq i}^{n_2}(K_{\gamma,y_i,y_j})^2-\frac{2}{n_1^2n_2^2}\sum_{i=1}^{n_1}\sum_{j=1}^{n_2}(K_{\gamma,x_i,y_j})^2\right] \tag{11}$$

which is a consistent estimator of $\sigma_0^2=2\left[\delta^{-1}+\delta+2\right]\left[E\left[f(X_i)\right]\right]\left[\int W^2(v)dv\right]$, the asymptotic variance of $\left(n_1n_2h_1...h_q\right)^{1/2}I_n$, where $\delta=\lim_{\min\{n_1,n_2\}\to\infty}\left(n_1/n_2\right)$. Under the alternative, the statistic diverges to $+\infty$, so the test is one-sided rejecting when the test statistics is sufficiently large.

A test using critical values taken from the asymptotic distribution shows finite-sample size distortions, so the npdeneqtest function (in program R, package np) employs bootstrap resampling to obtain the finite-sample distribution of the statistic (this provides a test having the correct size). We obtain the boot-strap resamples by resampling from the empirical distribution of the pooled data (i.e., are drawn from a multivariate normal distribution under the null). According to Racine (2012), bandwidths are obtained via likelihood cross-validation by default.

4 Data and results

We will illustrate using revenue DEA models under the assumption of a variable returns to scale, to measure the revenue and new revenue efficiency of commercial banks in the European countries. We assume 114 commercial banks located in 25 European countries. The data are taken for the period from 2010 to 2018. The source of the data is the Datastream database published by Thomson Reuters. These data were supported by Schumpeter School of Business and Economics at Bergische Universität in Wuppertal. Based on the literature review, we adopt the intermediation approach for selecting inputs and outputs of banks. The intermediation approach is the primary approach for modelling of banking activity, focusing in particular on the role of banks as financial intermediaries between depositors and end-users of bank assets. As mentioned by Sealey and Lindley (1977) deposits and other liabilities, together with real resources (labour and capital) are treated as inputs, whereas outputs include only bank assets that generate revenues such as loans and investments. We consider three inputs: The number of full-time employees (x_1), Total fixed assets in thousand of EUR (x_2), and Total deposits in thousand of EUR (x_3). We include two outputs: Total loans in thousand of EUR (y_1), and Total other earning assets thousand of EUR (y_2). Let denotes p_1 the price of output y_1, and p_2 the price of output y_2. The price of loans (p_1) in EUR can be calculated as the ratio of total interest income to total loans, and the price of other earning assets (p_2) in EUR can be calculated as the ratio of non-interest income to total other earning assets. Summary statistics of selected variables are presented in Table 1.

Table 1 Dataset – variables used for efficiency measurement

		x_1	x_2	x_3	y_1	y_2	p_1	p_2
2010	Min	102	241	113 452	40 512	90 915	0.01398	0.01054
	Max	295,061	217,615,000	5,821,489,000	8,013,575,000	2,225,845,526	0.16589	0.81328
	Aver.	26,585	3,637,618	177,493,360	262,660,353	162,797,917	0.04949	0.08438
	Std. dev.	54,003	20,453,369	593,685,041	845,482,279	377,362,896	0.02501	0.09568
2011	Min	144	837	207,704	69,722	145,028	0.01462	0.00380
	Max	288,316	82,245,000	6,398,853,000	8,531,408,000	2,895,505,957	0.17521	0.81328
	Aver.	26,631	2,433,804	187,789,283	276,907,313	182,574,531	0.05145	0.07686
	Std. dev.	54,054	8,145,135	645,754,523	905,494,125	438,033,415	0.02509	0.08529
2012	Min	140	635	278,503	107,174	161,588	0.01558	0.01022
	Max	286,019	81,524,000	6,550,708,000	7,975,233,000	2,650,380,543	0.17743	0.61036
	Aver.	25,938	2,459,322	191,324,836	266,875,597	189,188,766	0.05108	0.06979
	Std. dev.	52,374	8,128,634	656,039,810	849,037,422	442,524,591	0.02568	0.06826

Table 1 Dataset – variables used for efficiency measurement (continued)

		x_1	x_2	x_3	y_1	y_2	p_1	p_2
2013	Min	101	491	352,285	210,653	118,390	0.01225	0.00349
	Max	306,123	261,523,000	6,866,606,000	7,686,002,000	2,433,522,000	0.20770	0.60570
	Aver.	25,241	4,004,157	198,400,114	266,256,707	172,972,849	0.04956	0.06856
	Std. dev.	51,834	24,543,457	681,425,583	830,506,486	415,980,333	0.03016	0.06612
2014	Min	139	308	336,127	304,322	5,997	0.01066	0.00690
	Max	329,566	206,440,000	7,644,937,000	7,216,975,000	3,547,637,000	0.20524	5.57029
	Aver.	25,005	3,553,859	212,084,064	267,436,629	207,323,001	0.04575	0.10683
	Std. dev.	52,545	19,464,166	757,103,903	796,815,386	539,916,356	0.02767	0.51751
2015	Min	134	508	417,861	306,199	337,340	0.01198	0.00330
	Max	330,677	193,661,000	7,965,037,000	6,674,179,000	3,851,008,000	0.20279	0.23369
	Aver.	24,827	3,453,058	214,900,969	265,063,940	192,238,408	0.04193	0.05953
	Std. dev.	52,509	18,323,774	780,980,661	758,796,813	520,228,013	0.02816	0.03975
2016	Min	140	851	556,151	432,212	390,874	0.01204	0.00365
	Max	325,075	193,485,000	8,524,939,000	7,003,123,000	4,111,057,000	0.19675	1.01285
	Aver.	24,309	3,518,831	225,915,952	272,953,801	199,610,057	0.03844	0.06284
	Std. dev.	51,056	18,346,958	832,739,901	788,122,804	541,629,323	0.02656	0.09575
2017	Min	153	778	514,445	394,364	479,199	0.01266	0.00462
	Max	310,277	237,321,000	10,218,796,000	8,188,648,000	4,764,259,000	0.40918	1.01510
	Aver.	23,780	3,973,662	247,231,908	291,256,488	197,419,007	0.03930	0.05978
	Std. dev.	49,680	22,413,485	985,676,475	887,475,363	568,850,502	0.04275	0.09630
2018	Min	153	778	674,552	157,749	350,822	0.01187	0.00462
	Max	293,752	253,773,000	11,273,741,000	9,170,751,000	5,165,764,000	0.45173	0.62125
	Aver.	23,313	4,187,417	260,338,518	303,808,051	201,503,788	0.04204	0.06044
	Std. dev.	49,032	23,990,114	1,081,752,538	976,576,552	588,500,503	0.05498	0.08386
Total	Min	101	241	113,452	40,512	5997	0.01066	0.00330
	Max	330,677	261,523,000	11,273,741,000	9,170,751,000	5,165,764,000	0.45173	5.57029
	Aver.	25,070	3,469,081	212,831,000	274,802,098	189,514,258	0.04545	0.07211
	Std. dev.	51,733	19,031,631	791,927,818	847,819,579	495,855,359	0.03346	0.18849

Source: Prepared by authors

Practical calculation of revenue and new revenue efficiency is realised using the software RStudio, namely package 'Benchmarking', prepared by Bogetoft and Otto (2019). The results are presented in the following order. First, we report the estimates of traditional revenue and new revenue efficiency during 2010–2018. Next, we use univariate cross-tabulation to trace revenue and new revenue efficiency under the alternative classification based on different parameters like bank size and geographical region in Europe. As mentioned by Ray and Das (2010), the univariate approach does not satisfactorily analyse the distributional structure of the efficiency estimates. To address this aspect, the entire distribution of efficiencies based on kernel densities under various conditioning schemes is also presented.

Table 2 and Figure 2 present the results of revenue and new revenue model. When we look at the results of the traditional model, we cannot see dramatic changes during the analysed period. The median values were approximately at the same level with a slight decrease in 2014. As we can see under this approach, the efficient banks should be considered as outliers within the sample, as most of the efficiencies were located within the interval of 0.2–0.5. The minimum average value was reached in 2014, the maximum in 2017. The average revenue efficiency at the beginning of the analysed period was 36.24% indicating that on average, banks could increase their revenues by 63.76% by producing outputs in optimal combination under a given level of inputs. At the end of the analysed period, the average revenue efficiency was 38.58%, indicating potential revenue increase equal to 61.42%. Under the new revenue model, no outliers can be seen; the data are distributed between minimal and maximal values. We can see a relatively stable development until 2013, with a slight decrease between 2014 and 2016, which was replaced by an increase in the last two years. The minimum average value was reached in 2016, the maximum in 2013. The average new revenue efficiency at the beginning of the analysed period was 52.70% indicating that on average, banks could increase their revenues by 47.30% by producing outputs in optimal combination under while maintaining the given output prices and with a given level of inputs. At the end of the analysed period, the average new revenue efficiency was 52.79%, indicating potential revenue increase equal to 47.21%. Generally, based on the results, we can say that analysed banks were more efficient under the new revenue model than under the traditional revenue model. We can see that the levels of efficiencies are relatively low. Thus there is considerable room for improvement in productivity and profitability by efficient management in the sense of choosing proper combination of loan and investment portfolio and better resource management in day-to-day operations.

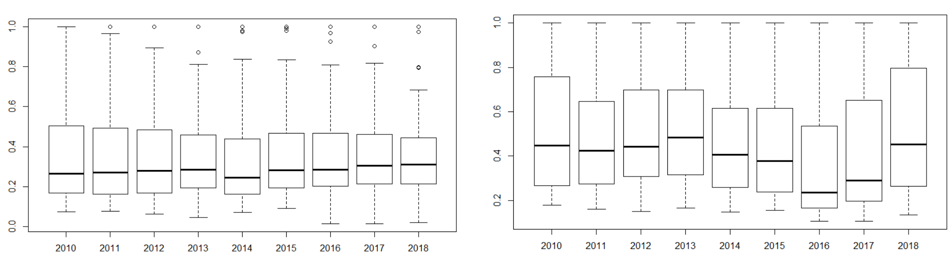
Table 2 Revenue efficiencies given by DEA models

Year	*No. of banks*	*Traditional revenue model*	*New revenue model*
2010	114	0.3624	0.5270
2011	114	0.3624	0.5062
2012	114	0.3693	0.5267
2013	114	0.3831	0.5499
2014	114	0.3574	0.4917
2015	114	0.3817	0.4632
2016	114	0.3825	0.3782
2017	114	0.3885	0.4270
2018	114	0.3858	0.5279
2010–2018	1026	0.3747	0.4886

Source: Prepared by authors

In the univariate approach, the estimates efficiencies were analysed by a single attribute. Table 3 and Figure 3 present the results of revenue and new revenue model in different geographical regions. The United Nations defines Eastern Europe as consisting of ten countries: Belarus, Bulgaria, Czech Republic, Hungary, Moldova, Poland, Romania, Russia, Slovakia and Ukraine. Northern Europe as consisting of the following ten countries: Denmark, Estonia, Finland, Iceland, Ireland, Latvia, Lithuania, Norway, Sweden and the UK. Countries that are part of Southern Europe are Albania, Andorra, Bosnia and Herzegovina, Croatia, Greece, Italy, Malta, Montenegro, North Macedonia, Portugal, San Marino, Serbia, Slovenia, Spain and Vatican City. Western Europe consists of the following nine countries: Austria, Belgium, France, Germany, Lichtenstein, Luxembourg, Monaco, Netherlands and Switzerland. Under both approaches, Northern Europe appeared as the most efficient. On the other hand, Southern Europe was ranked last. The generally lower efficiency of Southern and Eastern European banks can be explained by a couple of factors, above all, imprudent mortgage lending, non-performing loans of the past, lack of transparency and accountability in mortgage financing, shadow banking activities, failure of risk management systems, low systematic risk regulations and other reasons which led to the financial crisis in the American and European financial markets. The development of the average traditional revenue efficiency in four groups of banks indicated a decline in efficiency in the case of Northern Europe, while the efficiency in Eastern, Southern, and Western Europe increased. Under the new revenue model, the increase can be seen in the case of Eastern and Northern Europe, while the decrease can be seen in the case of Southern and Western Europe. When we look at boxplots according to geographical region, we can see that in the case of both models, the values were skewed towards lower values. The highest skew can be seen in the sample of banks from Southern Europe under the traditional revenue model. Based on our results, we can see some outlier values in traditional revenue efficiency calculated within the sample of Eastern, Southern, and Western European banks, and under the new revenue model within the banks located in Eastern and Southern Europe. We can also see that the highest variability can be seen in the sample of banks from Northern Europe under both models.

Figure 2 Revenue efficiencies given by DEA models according to years: (a) traditional revenue efficiency and (b) new revenue efficiency



(a) (b)

Source: Prepared by authors

The relationship between efficiency and size of banks is presented in Table 4 and Figure 4. The analysed banks were divided into three groups: small banks, medium-sized banks and large banks. In terms of absolute amounts, the threshold is defined based on the total assets of the analysed banks in the single year. Within the group of small-sized banks, there are banks with assets less than 0.01% of the total assets of analysed banks. Within the group of medium-sized banks, there are banks with assets between 0.01% and 0.5% of the total assets of analysed banks. Moreover, within the group of large-sized banks, there are banks with assets higher than 0.5% of the total assets of analysed banks.

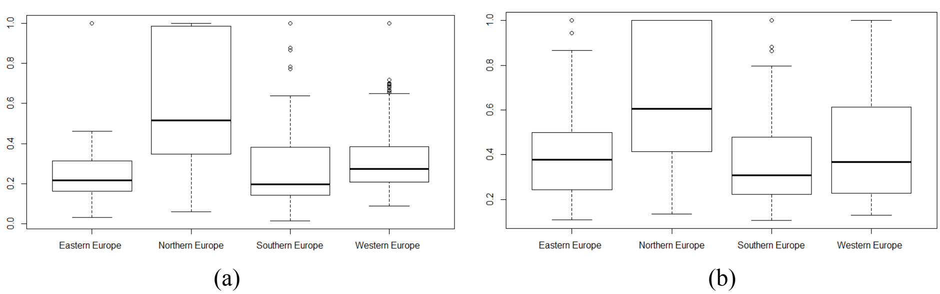
Also, the European Central Bank applies a similar methodology, but in this case, the thresholds are 0.005% and 0.5% of the total consolidated assets of EU banks.

Table 3 Geographical region and revenue efficiencies given by DEA models

Region (No. of banks)	*Traditional revenue model*				*New revenue model*			
Year	*Eastern Europe (N = 13)*	*Northern Europe (N = 26)*	*Southern Europe (N = 28)*	*Western Europe (N = 47)*	*Eastern Europe (N = 13)*	*Northern Europe (N = 26)*	*Southern Europe (N = 28)*	*Western Europe (N = 47)*
2010	0.2662	0.6285	0.2553	0.2978	0.4231	0.7119	0.4292	0.5057
2011	0.2663	0.6240	0.2628	0.2960	0.4157	0.6400	0.4477	0.4879
2012	0.2739	0.5674	0.3078	0.3174	0.4347	0.6349	0.4589	0.5289
2013	0.3032	0.5923	0.2919	0.3374	0.4728	0.7018	0.4538	0.5392
2014	0.2790	0.5611	0.2605	0.3177	0.4427	0.6473	0.3842	0.4777
2015	0.2923	0.5756	0.2810	0.3529	0.4181	0.6210	0.3526	0.4485
2016	0.2931	0.5875	0.2626	0.3583	0.3403	0.5915	0.2705	0.3281
2017	0.3009	0.5790	0.2877	0.3613	0.3865	0.6387	0.2984	0.3905
2018	0.3047	0.5731	0.2728	0.3655	0.4880	0.7226	0.4111	0.4941
2010-2018	0.2866	0.5876	0.2758	0.3338	0.4246	0.6566	0.3896	0.4667

Source: Prepared by authors

Figure 3 Revenue efficiencies given by DEA models according to geographical region: (a) traditional revenue efficiency and (b) new revenue efficiency



Source: Prepared by authors

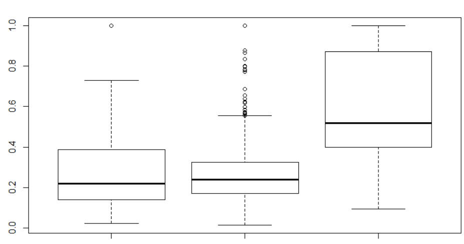
The results indicate that large banks were more efficient than small and medium-sized banks. The last efficient were medium-sized banks under both approaches. In the case of large banks, the minimum average value of traditional revenue model was reached in 2010, the maximum in 2015. The average revenue at the end of the analysed period was 58.95%, indicating potential revenue increase by 40.05%. In the case of the medium-sized banks, the minimum was reached in 2014 and a maximum in 2012. In the case of the small banks, the minimum was reached in 2011 and a maximum in 2017. In the case of the medium-sized and large banks approximately the same level of efficiency can be seen at the beginning and at the end of the analysed period, while improvement can be seen in the case of small banks. The different situation can be seen under the new revenue model, where improvement can be seen in the case of large banks. When we look at boxplots according to the size of banks, we can see that in the case of both models, the values were skewed towards lower values. The highest skew can be seen in the sample of small banks under the new revenue model. Based on our results, we can see some outlier values in traditional revenue efficiency calculated within the sample of small and medium-sized banks, and under the new revenue model within the medium-sized banks. We can also see that the large banks were more efficient than the medium-sized. The highest variability can be seen in the sample of small banks under the new revenue model.

Table 4 Bank size and revenue efficiencies given by DEA models

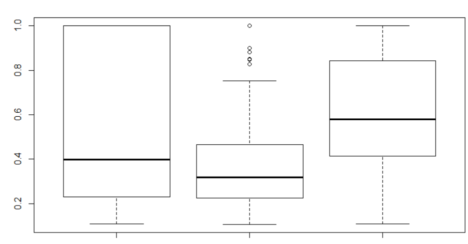
Region (No. of banks)	*Traditional revenue model*			*New revenue model*		
Year	*Small banks (N = 30)*	*Medium-sized banks (N = 54)*	*Large banks (N = 30)*	*Small banks (N = 30)*	*Medium-sized banks (N = 54)*	*Large banks (N = 30)*
2010	0.3019	0.2716	0.5865	0.6050	0.4077	0.6639
2011	0.2998	0.2652	0.6001	0.6309	0.3923	0.5864
2012	0.3021	0.2838	0.5905	0.6753	0.4138	0.5813
2013	0.3666	0.2746	0.5950	0.6704	0.4385	0.6299
2014	0.3265	0.2419	0.5961	0.5706	0.3822	0.6099
2015	0.3483	0.2771	0.6035	0.5062	0.3551	0.6147
2016	0.3745	0.2717	0.5899	0.3651	0.2725	0.5817
2017	0.3870	0.2778	0.5895	0.4610	0.3049	0.6129
2018	0.3778	0.2780	0.5877	0.6061	0.3996	0.6805
2010-2018	0.3427	0.2713	0.5932	0.5656	0.3741	0.6179

Source: Prepared by authors

Figure 4 Revenue efficiencies given by DEA models according to bank size: (a) traditional revenue efficiency and (b) new revenue efficiency



(a)



(b)

Source: Prepared by authors

The results presented by the boxplots provided the analysis of entire distributions. We now turn to the analysis of the distribution of revenue and new revenue efficiency. We apply the test presented by Li et al. (2009), to compare if there exist significant differences between both approaches, and also between different size groups and groups according to geographical location.

The comparative analysis of the different European regions performed in Table 5 reveals that there exist significant differences between the efficiencies of banks in different regions at a 1% level. The significant differences did not exist when comparing banks from the Eastern and Southern Europe in both models. In this particular case, the discrepancies are never significant at a 5% level. As we know, a higher value of T-statistics can signify more significant differences between regions. Based on this assumption, we can say that the most significant differences were between banks from the Eastern and Northern Europe in both models. Based on the results, we can generally say that it depends on whether the bank is located in Northern, Western, Southern, or Eastern Europe. So we can confirm our research hypothesis that it depends on the location of the bank.

Table 5 Distribution hypothesis tests by geographical region

		Traditional revenue model	*New revenue model*
f(East) = *g*(North)	T-statistics	37.5183	35.7811
	p value	0.0000	0.0000
f(East) = *g*(South)	T-statistics	2.4125	6.5066
	p value	0.0526	0.0677
f(East) = *g*(West)	T-statistics	5.8389	29.0596
	p value	0.0201	0.0100
f(North) = *g*(South)	T-statistics	34.7418	22.3414
	p value	0.0000	0.0000
f(North) = *g*(West)	T-statistics	28.7375	13.7789
	p value	0.0000	0.0000
f(South) = *g*(West)	T-statistics	15.072	17.2492
	p value	0.0000	0.0000

The functions *f*(·) and *g*(·) are (kernel) distribution functions for each model being compared.

Source: Prepared by authors

Results in Table 6 account for significant differences between the efficiencies of banks in different size groups at a 1% level. The significant differences can be seen in the case of traditional and new revenue model in a whole sample. Based on the results of this analysis, we can, therefore, say that it depends on whether the bank is large, medium-sized or small. So we can confirm our research hypothesis that it depends on the size of the bank.

In the last part of our paper, we try to compare the differences between efficiencies calculated using two main models – traditional revenue efficiency (TRE) and new revenue efficiency (NRE) – in the whole sample, in different regions, and different sized groups. Based on the results presented in Table 7, we can see that there exist significant differences between efficiencies calculated by TRE and NRE model. The exception is in case of banks in Northern Europe and banks in large size group. In these two cases, the differences are not significant, so we can claim that both models produce comparable results.

Table 6 Distribution hypothesis tests by bank size

		Traditional revenue model	*New revenue model*
f(Large) = *g*(Medium-sized)	T-statistics	61.2330	22.2613
	p value	0.0000	0.0000
f(Large) = *g*(Small)	T-statistics	24.1891	50.9401
	p value	0.0000	0.0000
f(Medium-sized) = *g*(Small)	T-statistics	25.2383	69.4386
	p value	0.0000	0.0000

The functions *f*(·) and *g*(·) are (kernel) distribution functions for each model being compared.

Source: Prepared by authors

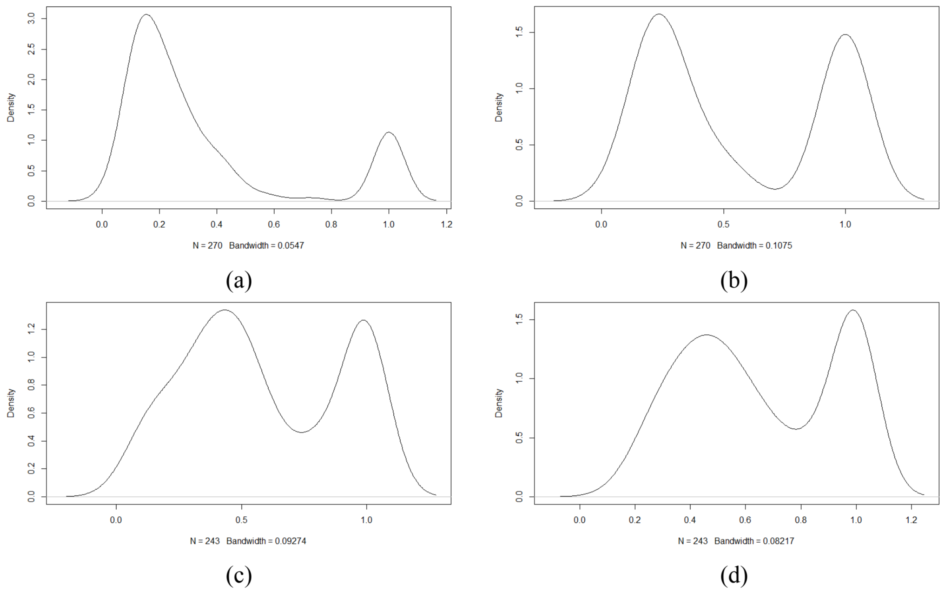
Table 7 Distribution hypothesis tests by applied model

		All years
f(TRE) = *g*(NRE)	T-statistics	9.2694
	p value	0.0000
f(TRE, East) = *g*(NRE, East)	T-statistics	9.2753
	p value	0.0000
f(TRE, South) = *g*(NRE, South)	T-statistics	16.1473
	p value	0.0000
f(TRE, North) = *g*(NRE, North)	T-statistics	–3.49795
	p value	0.4962
f(TRE, West) = *g*(NRE, West)	T-statistics	22.6515
	p value	0.0000
f(TRE, Large) = *g*(NRE, Large)	T-statistics	9.8949
	p value	0.4261
f(TRE, Medium-sized) = *g*(NRE, Medium-sized)	T-statistics	16.9593
	p value	0.0000
f(TRE, Small) = *g*(NRE, Small)	T-statistics	60.4317
	p value	0.0000

The functions *f*(·) and *g*(·) are (kernel) distribution functions for each model being compared.

In other sub-groups, it depends on whether the efficiency is calculated by using the traditional or new revenue model. As we know, a higher value of T-statistics can signify more significant differences between sub-groups. Based on this assumption, we can say that the most significant differences were between efficiencies calculated by TRE and NRE model within the banks located in the small-sized group (Figure 5(a) and (b)). As we can see in the previous table, the significant differences do not exist between efficiencies calculated by TRE and NRE model within the banks located in Northern Europe. It can also be seen in Figure 5(c) and (d). So we can confirm our research hypothesis that it depends on the applied methodology. As we can see that different method bring significantly different results, therefore it is better to use several methods simultaneously instead of a single method and try to find out models which describe the real situation in the best way.

Figure 5 Density distribution: (a) traditional revenue efficiency – small banks; (b) new revenue efficiency – small banks; (c) traditional revenue efficiency – Northern Europe and (d) new revenue efficiency – Northern Europe



Source: Prepared by authors

5 Conclusion

Using the nonparametric DEA method, this paper empirically estimates the efficiencies of banks in Europe during the period from 2010 to 2018. The original contribution of the paper is an illustrative application of the traditional Farrell (1957) DEA approach as well as a new Tone (2002) approach for evaluating the revenue efficiency of the commercial banks. From the gained results it comes out that, in the case of the traditional approach, which assumes that prices of outputs are exogenously given and also in the case when prices of outputs are added, the transformation of deposits into loans and other earning assets was successfully achieved by the larger ones on the market, and also by bank located in Northern Europe.

When we look at the results of the traditional revenue model and a new revenue model, we cannot see dramatic changes during the analysed period. The average traditional revenue efficiency ranged from 35.74% to 38.85%, and average new revenue efficiency ranged from 37.82% to 54.99%. The results of the analysis in European regions show that the average level of efficiencies in the case of banks located in Northern and Western Europe was above than the total average and the average efficiencies in the case of banks located in the Southern and Eastern Europe were below the total average under the traditional revenue model. Under the new revenue model, only banks located in Northern Europe obtain average efficiency higher than the average of the whole sample. Results of the analysis in three sized groups pointed to the fact that the large banks seem to be most efficient while the medium-sized banks were the least efficient under both approaches.

In the last part of our paper, we examined whether there exist significant differences in estimated efficiencies. Specially, we focused on four sources of heterogeneity, namely, the type of efficiency considered (traditional or new revenue model), the location of the bank (Northern, Western, Southern or Eastern Europe), and the size of the bank (large, medium-sized, or small). Based on the results of distribution hypothesis tests, we could confirm our research questions that depended on size, location and applied methodology. By performing the nonparametric test for equality of densities prepared by Li et al. (2009), we fill the gap in the existing scientific literature by studying the differences between the efficiencies of banks measured by the nonparametric method, DEA. As the results of our analysis pointed to the existence of significant differences between banks, therefore in the future research, we would like to apply the panel regression analysis to determine which factors had a positive or negative impact on the revenue efficiency. We want to include not only parameters like bank size, and location, but also extend our analysis with another bank variable as well as macroeconomic and regulatory variables.

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