Journal Homepage: -www.journalijar.com

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)

RESEARCH ARTICLE

MEASURING THE EFFICIENCY OF EUROPEAN BANKS: A DIRECTIONAL DISTANCE FUNCTION APPROACH.

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Manuscript Info	*Abstract*
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The aim of this paper was to estimate the technical efficiency of 423 European banks during the period 2013–2015 while simultaneously dealing with discretionary, non-discretionary, desirable, and undesirable factors. The author used the Directional Distance Function approach. Particularly, he considered the fixed assets as a non-discretionary input and the non-performing loans as an undesirable output. The empirical results revealed significant effects on inefficiency measures in comparison to those obtained when excluding undesirable outputs. Moreover, the outcomes showed an increasing level of the average inefficiency for most European countries. These outcomes confirmed the persistence of the negative impact of the financial crises and the inability of the European banking system to really recover from these crises.

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Introduction:-
It is well acknowledged that efficiency models significantly depend on the mixture of used inputs and outputs. Indeed, different input/output combinations generate different efficiency scores. Furthermore, a given decision making unit (DMU) may or may not be efficient depending on the selected input/output combination. Hence, deciding which inputs and outputs the model should take into consideration is particularly important in the efficiency assessment process.

Due to the absence of an exact expression of the banking production function and of the factors that may explain the performance of a given bank, we conjecture that more than a single inputs/outputs combination should be used to evaluate efficiency in order to obtain a better and a more complete picture of a bank performance and also to detect relevant factors on which correcting actions have to be undertaken. However, these inputs/outputs can be classified to four groups: discretionary, non-discretionary, desirable, and undesirable factors.

Evaluating banks efficiencies using models with discretionary and desirable inputs/outputs have been widely studied. Nevertheless, there still lacks of more investigation on banks efficiencies while considering both non-discretionary and undesirable variables. Indeed, in the banking context, almost all previous studies take into account only discretionary inputs and desirable outputs. These studies assume that each bank seeks to improve its results by better controlling the amounts of its inputs or outputs. Nevertheless, in the reality many variables are beyond the managerial control. Moreover, some variables may be uncontrollable within a short-term period. The adjustment

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bank ability depends on the time period needed for modification long- or short-run horizon. Factors that cannot be varied in the short run should be treated as non-discretionary also known as fixed or quasi-fixed variables.

In this study, we propose to use the DDF method to estimate the technical efficiency of European banks. The main argument for using a non-parametric approach rather than parametric technique is that it can be easily put into practice without prior knowledge of the frontier form. Moreover, the DDF approach is able to handle simultaneously desirable/undesirable outputs as well as discretionary/non-discretionary inputs. It can also produce robust results when used to estimate the frontier of efficiency as confirmed by many previous studies. Furthermore, we develop three different models specification in order to illustrate the impact of taking into account the undesirable outputs and the non-discretionary inputs in the assessment of efficiency scores.

The rest of the paper is structured as follows. Section 2 presents a brief review of previous studies. Section 3 presents the adopted methodology. Section 4 illustrates the procedure through a real-world banking data example. Section 5 displays the results and some discussions. Section 6 concludes.

Literature review
Substantial attention has been given to banking efficiency measurement and analysis. Some authors offer interesting and wide-ranging reviews such as Hughes and Mester (2015), Fethi and Pasiouras (2010), Berger and Mester (2003), and Berger and Humphrey (1997). The majority of the previous studies use either the Data Envelopment Analysis (DEA) or the Stochastic Frontier Analysis (SFA). Only recently, some studies start adopting the DDF methodology (initiated by Chung et al., 1997).

Furthermore, Most previous efficiency-banking studies have considered only factors that are under managerial control (discretionary inputs and outputs). Fujii et al. (2018), Kamarudin et al. (2017), Lee and Huang (2017), Tan and Anchor (2017), Subramanyam (2016), Tsionas et al. (2015) are some examples of such studies. Having noticed that non-discretionary factors may influence efficiency scores, two different frameworks have been adopted to address this issue. The first framework is based on Banker and Morey (1986)'s model. It considers directly the non-discretionary variables in the assessment process. While the second framework accounts for non-discretionary variables in a second stage in order to detect whether these variables have an effect on the achieved efficiency scores. Specifically, the assessed efficiency scores obtained in a first stage are explained in particular through these non-discretionary variables using a regression analysis, such as the ordinary least squares and the Tobit regression. Rouse et al. (1996) state that the outcomes of these two frameworks are significantly different.

Hunter and Timme (1995) handle a sample of 254 US commercial banks over the period 1984-1987 to evaluate their efficiency while treating the core deposits and the number of branches as quasi-fixed inputs. Based on the obtained results, the authors assert that ignoring quasi-fixed nature of some inputs may generate biased results. To investigate the impact of regulation on efficiency level, Färe et al. (2004) compare the estimated profit inefficiency scores obtained using two DDF models for a sample of US banks while considering non-discretionary inputs. The first one assumes equity and off-balance sheet activity as non-controllable inputs (these inputs correspond respectively to the risk-based capital and the leverage regulation constraints). However, the second model treats the leverage ratio as the only non-discretionary input. Mavi et al. (2013) take into account a non-discretionary input in the evaluation of the efficiency of bank branches. For this, they apply the common set of weights method to 20 Iranian bank branches while considering the distance of each branch to the city as the non-discretionary input. Menicucci and Paolucci (2016), Aktas et al (2015), Gishkori and Ullah (2013), Raphael (2013), Pasiouras et al. (2011), and Casu and Molyneux (2003) study the impact of the size (non-discretionary variable) among other variables on efficiency scores by adopting the multi-stage methodology.

Recently researchers attribute much more attention to undesirable-outputs issue. Hamid et al. (2017), Huang and Chung (2017), Lozano (2016), Aghayi and Maleki (2016), Cheng and Zervopoulos (2014), Jayaraman and Srinivasan (2014), Glass et al. (2014), Barros et al. (2012), and Fukuyama & Weber (2008) have treated non-performing loans (NPLs) as an undesirable output in bank efficiency measurement and support that ignoring bad outputs is misleading. Fujii et al. (2014) and Assaf et al. (2013) display that we need to integrate NPLs in the assessment process otherwise we obtain biased results. Curi et al. (2013) strongly affirm that the omission of NPLs from the assessment process might generate underestimated efficiency scores. In fact, without including NPLs in the model, a high efficiency score for a given bank does not necessarily indicate a better performance than other banks; it might be done at the expense of making a high proportion of undesirable outputs. By estimating the efficiency of

52 Taiwanese commercial banks over the period 1999-2012, Huang and Chung (2017) establish as well that ignoring NPLs from the evaluation process tends to overestimate the inefficiency scores.

To deal with undesirable outputs, researchers generally choose one between two approaches. Either they apply the traditional parametric and non-parametric methodologies after performing a prior transformation on the undesirable output, or without any transformation of the undesirable outputs they use the DDF methodology.

Among techniques that can be applied to deal with the amount of bad output is using a decreasing function by considering the undesirable output as an input or deducing the undesirable output value from a relative good output. More discussion and details are given in Scheel (2000). For instance, in the case of NPLs, previous studies either treat them as an input to be reduced as much as possible or deduce them from gross loans and then use obtained net loans as a good output to be maximized as much as possible. Sufian (2007) appraises the efficiency of 17 Malaysian Islamic banks over the period 2001-2005 using Data envelopment analysis approach while taking into account the NPLs as inputs. Pan et al. (2010) among other studies affirm that such approaches provide biased results. Drake and Hall (2003) while considering the provisions for loan losses as an input in the evaluation process of the efficiency of a sample of Japanese banks, they show that the overall average efficiency scores have almost significantly increased alongside the number of efficient banks has almost doubled compared to the case where this undesirable variable is ignored.

Recently, some researchers have adopted the second approach based on the DDF methodology. It allows the accommodation of the undesirable outputs in their initial form. Hamid et al. (2017) adopt a DDF approach to assess the efficiency of 21 commercial banks in Malaysia over the period 2005-2014 while considering NPLs as the only bad output. Huang et al. (2015) under a stochastic framework apply a new meta-frontier directional distance function to appraise the efficiency of 17 banking systems in the Central and Eastern European countries. To do this, they identify three discretionary inputs, three good outputs and the NPLs as a bad output. Moreover, they perform a likelihood ratio test to show the non-significance of the efficiency results when the undesirable output is ignored. Jayaraman and Srinivasan (2014) assess as well the technical inefficiency for a sample of Indian banks over the period 2005-2012 using a DDF approach based on a database of four inputs, two outputs and one undesirable output (Non-performing assets). Aghayi and Maleki (2016) use as well the DDF approach while treating the undesirable output as input. They apply the obtained model to a sample of 52 branches of the Iranian National Bank over the period 2011-2014, using two inputs: deposits and interest rate on each loan to produce four good outputs and a bad output (NPLs). Through a hyperbolic distance function, Mamatzakis et al. (2016) appraise for a sample of Japanese commercial banks over the period 2000-2013, the efficiency scores using a data for three discretionary inputs, two good outputs and two undesirable outputs; namely, the problem loan and the non-loan assets.

Based on this brief literature review, we can notice that despite the large number of empirical studies investigating on banking efficiency assessment, those that have explored banking efficiency evaluation using a DDF methodology still to be restricted. Furthermore, to our knowledge, there is no study that has applied DDF while taking into account simultaneously both non-discretionary inputs and undesirable outputs. Moreover, more investigations still to be required in the context of the Eurozone banking system particularly post the sovereign debt crisis.

Methodology:-

Let us consider a production activity using a set of m_1 discretionary inputs, $X = \{X_i, i = 1, \dots, m_1\}$, and m_2 non-discretionary inputs, $Z = \{Z_i, i = 1, \dots, m_2\}$, employed to produce jointly a vector of s desirable outputs, $y = \{y_r, r = 1, \dots, s\}$, and a vector of d undesirable outputs, $b = \{b_u, u = 1, \dots, d\}$. The production technology is defined as

$$\Psi = \{(x, z, y, b) \in \Re_+^{m_1+m_2+s+d} \,|\, (x, y) \, can \, produce \, (y, b)\}$$

We consider a production activity using a set of discretionary and non-discretionary inputs to produce jointly a vector ofdesirable and undesirable outputs. Based on production theory (Färe and Grosskopf, 2006), the production technology set is assumed to be closed, convex and nonempty. In addition, we assume strong (free) disposability for both discretionary inputs and desirable outputs. However, we assume weak disposability of non-discretionary inputs and undesirable outputs. Free disposability for discretionary inputs indicates that the quantity of any given discretionary input can be increased while holding other inputs and outputs constant. Weak disposability assumption of non-discretionary inputs states that a proportional increase in the inputs can yield the production of the same

amount of outputs.Strong disposability of desirable outputs implies that if a given desirable and undesirable output vector is feasible then any output vector with a reduced quantity of desirable output is also feasible. Weak disposability of undesirable outputs means that proportional reductions of good and bad outputs are feasible. Weak disposability implies that it is costly to reduce bad outputs. For example, if a bank wants to reduce the amount of NPLs, it would be brought to make fewer loans. This assumption is complemented with the Null-jointness assumption. This later says that we cannot produce desirable outputs without producing undesirable ones. For example, if a bank does not want to produce NPLs, it would be led to not produce any loan.

To evaluate the output oriented inefficiency measure for a given bank, we use the DEA estimator under variable return to scale to obtain a measure of the distance function. Furthermore, in order to investigate the impact of considering non-discretionary inputs and undesirable outputs in the assessment process we estimate three different models M_1, M_2, and M_3. In addition to the conventional inputs and outputs, M_1 accounts for both non-discretionary inputs and bad outputs. M_2 differs from M_1 only by treating all inputs as discretionary ones. M_3 considers all inputs as discretionary and takes into account only desirable outputs. The inputs and outputs of M_3 are similar to those of M_2 after ignoring the undesirable output. More specifically, model M_2 is developed in order to analyze the effect of ignoring the non-discretionary nature of the input. However, model M_3 is designed to study the effect of ignoring the undesirable output. To evaluate the output oriented inefficiency measure for a given bank according the three models, we use respectively the following three DEA estimators under variable return to scale to obtain a measure of the corresponding distance function.

$$\overrightarrow{D}_1(x,z,y,b;g) = \hat{\beta}_1 = \max\left\{\beta \middle| x \geq \sum_{j=1}^{j=n}\lambda_j x_j, z = \sum_{j=1}^{j=n}\lambda_j z_j, y + \beta y \leq \sum_{j=1}^{j=n}\lambda_j y_j, \right.$$
$$\left. b - \beta b = \sum_{j=1}^{j=n}\lambda_j b_j, \sum_{j=1}^{j=n}\lambda_j = 1 \; \forall \; j = 1,\ldots,n\right\}$$

$$\overrightarrow{D}_2(x,y,b;g) = \hat{\beta}_2 = \max\left\{\beta \middle| x \geq \sum_{j=1}^{j=n}\lambda_j x_j, y + \beta y \leq \sum_{j=1}^{j=n}\lambda_j y_j, \right.$$
$$\left. b - \beta b = \sum_{j=1}^{j=n}\lambda_j b_j, \sum_{j=1}^{j=n}\lambda_j = 1 \; \forall \; j = 1,\ldots,n\right\}$$

$$\overrightarrow{D}_3(x,z,y;g) = \hat{\beta}_3 = \max\left\{\beta \middle| x \geq \sum_{j=1}^{j=n}\lambda_j x_j, y + \beta y \leq \sum_{j=1}^{j=n}\lambda_j y_j, \sum_{j=1}^{j=n}\lambda_j = 1 \; \forall \; j = 1,\ldots,n\right\}$$

Data

The dataset used in this study is obtained from the Orbis Bank focus previously called Bankscope database compiled by Van Dijk Electronic Publishing Bureau. Our sample is composed of 423 commercial banks from 27 EU countries covering the period 2013-2015. Obviously, our sample is large enough to certify robustness of the obtained efficiency scores. We use three inputs and three outputs. The inputs are universally adopted in several studies: labor (personnel expenses), funds (total deposits), and capital (Fixed assets), while the outputs are loans (net loans = Total loans – Non-performing loans), other assets, and NPLs. To measure banks efficiency, many authors believe that deposits and loans are key variables in DEA model. Within model M_1, we treat the capital as non-discretionary input since it cannot be altered in a short-term horizon. However, in order to investigate the impact of this treatment, we handle capital as controllable for model M_2. Finally, in order to examine the impact of ignoring the undesirable outputs, we develop model M_3 in which we consider only discretionary inputs and good outputs. Below, Table 1 summarizes the selected inputs and outputs variables for each developed model and Table 2 displays descriptive statistics of the selected inputs and outputs variables of the pooled sample.

Results and Discussion:-

All the results of the efficiency analysis were obtained using SAS software. The obtained values can be interpreted as the inefficiency level of a given bank according to each model. A score equal to zero designates that the bank is efficient however a value greater than zero indicates that the bank is inefficient. For example according to M_1, the bank 100 had an inefficiency of 0.044 which means that to operate efficiently, the bank should expand its net loans by 0.044*233,852602=10,289514; expand its other assets by 0.044*26,273711=11,760043; and contract its NPLs by 0.044*14899796=655591, while using the same quantities of labor, deposits, and capital.

The findings exhibited that the average inefficiency scores have increased over the studied period according to all models with a small drop for M_3 on 2014. Table 3, below, shows some descriptive statistics of technical inefficiency

scores for the three models. In particular, it shows that in 2013 the inefficiency problem touches 86.29% of banks according to M_1.

Table 1:-Overview of inputs and outputs for each model.

Model name	Model 1	Model 2	Model 3
Input 1: Labor	✓	✓	✓
Input 2: Deposits	✓	✓	✓
Input 3: Fixed assets as non-discretionary	✓		
Input 3: Fixed assets as discretionary		✓	✓
Output 1: Net loans	✓	✓	✓
Output 2: Other assets	✓	✓	✓
Output 3: NPLs as bad output	✓	✓	

Table 2:-Descriptive statistics of selected inputs and outputs.

Year	**2013**	**2014**	**2015**
Input variables			
Labor	583 787	527 594	483 424
	(2 109 332)	(1 878 941)	(1 737 916)
Funds	507 295	464 685	457 667
	(2 025 904)	(2 004 045)	(2 149 052)
Non-discretionary input			
Capital	51 020 903	45 006 473	40 753 994
	(157 268 170)	(139 390 249)	(127 584 790)
Output variables			
Loans	38 137 914	34 492 403	31 946 433
	(112 174 422)	(102 930 270)	(96 119 394)
Other assets	37 436 892	34 537 001	29 072 466
	(155 166 582)	(146 935 536)	(117 908 166)
Undesirable output			
Non-performing loans	3 330 954	2 650 809	2 119 241
	(9 714 039)	(7 852 789)	(6 545 897)

It also displays 39, 41, and 40 efficient banks according to M_3; however, it shows 58, 61, and 56 efficient banks according to M_1 respectively during 2013, 2014, and 2015. These beforehand mentioned banks constituted the best-observed practice frontier and were used as references for inefficient ones. In addition, Table 3 shows in line with Drake and Hall (2003) that the efficiency scores had significantly improved together with an increase of the number of efficient banks compared to the case where the NPLs were ignored as an undesirable output.

Furthermore, the results showed that M_3 had the highest technical inefficiency scores over the examined period, while there was only a slight difference between the results of the two first models differing in the specification of fixed assets as discretionary or non-discretionary input. This leads us to wonder whether the use of fixed asset as a non-discretionary input makes a significant difference if this input was treated as discretionary.

Table 3:-Summarystatistics of inefficiency scores.

Inefficiency	Year	Mean	Std. Dev.	Min	Max	Number Efficient	Percent Efficient
$\hat{b}_1$	2013	0.662	0.349	0	0.999	58	13.71
	2014	0.699	0.356	0	0.997	61	14.42
	2015	0.741	0.349	0	0.999	56	13.24
$\hat{b}_2$	2013	0.663	0.347	0	0.999	56	13.24
	2014	0.702	0.353	0	0.997	57	13.47
	2015	0.745	0.344	0	0.999	52	12.29
$\hat{b}_3$	2013	3.756	3.559	0	18.489	39	9.21
	2014	3.124	2.586	0	18.447	41	9.69
	2015	4.076	2.886	0	13.135	40	9.46

Did it make significant difference when using fixed assets as non-discretionary?
To answer this question, we propose to test if this slight difference between the scores of the first two models is statistically significant. That is why; we performed three non-parametric tests; namely, the Pearson's Correlation, Wilcoxon matched-pairs signed-rank tests, and the two-sample Kolmogorov-Smirnov test as displayed in Table 4.

First, we performed the Pearson's Correlation test to identify if there were any correlation relationship between the scores of M_1 and that of M_2. This test permits to evaluate the strength of a linear relationship between the scores of the two models. As shown in Table 4, the correlation is very high and almost equal to 1 with p-values less than 1% obtained over the entire period (statistically significant at the level of 1%). We therefore rejected the hypothesis that the correlation is equal to 0.

Second, we applied the Wilcoxon matched-pairs signed ranks test to examine the equality of the corresponding distribution functions of the inefficiency scores obtained via the two Models M_1 and M_2. It is a non-parametric test that does not require any assumptions regarding the form of the distributions. The p-values shown in Table 4 allowed us to accept the null hypothesis asserting that we did not have compelled evidence that the two distributions differ.

Finally, the Two-sample Kolmogorov-Smirnov test strengthened the results of the two previous tests. Indeed, as exposed in Table 4 the related p-values revealed that it is reasonable to assume that the inefficiency scores lists came from the same distribution and hence M_1 and M_2 provided significantly the same results, over the three years.

Table.4:-Did it make significant difference when using the fixed assets as non-discretionary?

Year	Pearson		Wilcoxon	Kolmogorov-Smirnov
	Correlation	p-value	p-value	p-value
2013	0.999	< 2.2e-16***	0.9747	1
2014	0.999	< 2.2e-16***	0.9615	1
2015	1	< 2.2e-16***	0.9436	1

*** Indicate significance at the level of 0.01.

Therefore, we concluded that treating the fixed assets as non-discretionary makes no significant difference with the case where they were treated as discretionary. This last result is in line with that of Färe et al. (2004) who had shown that the distribution function of inefficiency obtained when considering both equity and off-balance sheet activities as fixed inputs was the same as the distribution function of inefficiency found when only off-balance sheet was treated as fixed input. These obtained results may explain the reasons behind which most previous studies did not consider such inputs as non-discretionary as discussed previously. In the following, discussions and analyses will focus on the results of M_1 and M_3.

Did it make any significant difference when ignoring NPLs as undesirable outputs?
By comparing the results of M_1 and M_3, the findings confirmed the sensitivity of efficiency scores to the specification of outputs and inputs. Furthermore, the results displayed that every time a given bank was inefficient according to M_1, it was also inefficient with regard to M_3. In addition, each time a bank was efficient according to M_3; it was efficient with regard to M_1. Moreover, the inefficiency scores had considerably changed according to M_3. This may confirm that ignoring NPLs tends to overestimate the inefficiency scores and that only models handling both desirable and undesirable outputs, can produce robust results as was previously advocated by Eskelinen (2017), Fujii et al. (2014), Assaf et al. (2013), and Curi et al. (2013). That is why; in the following we limit our discussion mainly on the outcomes of M_1.

Barros et al. (2007) indicated that location among other factors might influence the performance of banks in the EU. Table 5 offers the average inefficiency scores for each country over the studied period. Accordingly, the average inefficiency scores of M_1range from 0.435 (Finland) to 0.98 (Romania), while those of M_3 vary from 1.0170303 (Ireland) to 8.2418753 (Romania) suggesting the inexistence of fully inefficient country (with a score equal to zero). For both models Romania appears to be the less efficient country, which indicates that the Romanian banks' managerial ability requires large room for improvement.

Moreover, when analyzing the scores of each country over the whole period, the outcomes suggest that almost all banking systems had suffered from a drop of their efficiency scores as shown below in Fig 1. This finding is in line

with those of Degl'Innocenti et al. (2017) and Kevork et al. (2017) claiming that after 2010 European banks efficiency scores had decreased following the sovereign debt crisis.

Table 5:-Average technical inefficiency scores by country over time according to M_1 and M_3.

Countries	Average	
	Model 1	Model 3
Austria	0,7921239	2,7507132
Belgium	0,7297719	2,2921387
Bulgaria	0,8839328	4,7333659
Croatia	0,9518965	5,9849131
Cyprus	0,9193225	4,8925948
Czech Republic	0,806252	3,3142781
Denmark	0,76771	5,3949048
Estonia	0,7637154	5,9648991
Finland	0,4355487	2,6985982
France	0,6910367	4,05312
Germany	0,5059086	2,5505892
Greece	0,9416579	3,3179254
Hungary	0,8174911	4,7178558
Ireland	0,5680794	1,0170303
Italy	0,7107336	2,9196957
Latvia	0,8715223	4,5762584
Luxembourg	0,5915674	1,9625012
Malta	0,9252946	6,1641563
Netherlands	0,5376187	2,3553529
Poland	0,8500325	4,1164289
Portugal	0,7918188	3,1709703
Romania	0,9800407	8,2418753
Slovakia	0,9422211	4,8611779
Slovenia	0,9551607	5,9905995
Spain	0,6110115	1,6007011
Sweden	0,4635567	3,3425288
United Kingdom	0,4648796	2,5551082
Average	0,7507373	3,9088993
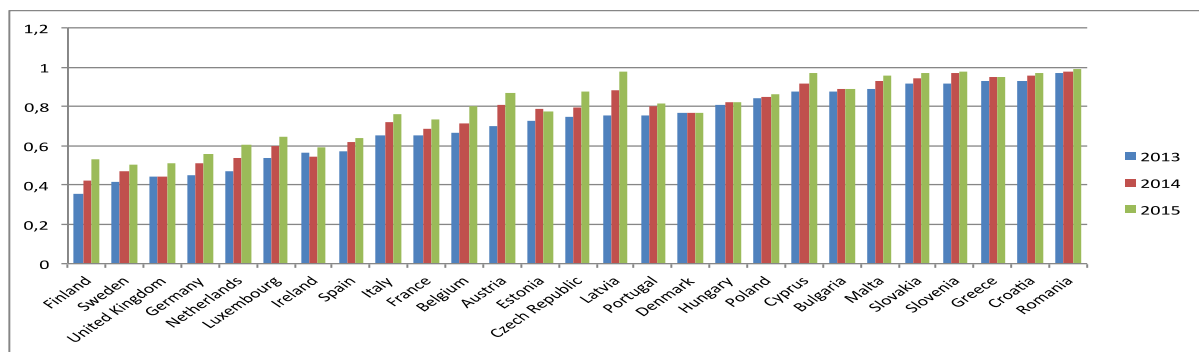
Fig 1:-Evolution of the inefficiency scores per country over the period 2013-2015.

The inefficiency increase may be in particular explained by the continuing piling up during the studied period of NPLs by Eurozone banks as displayed in Fig 2, especially, the banks in Cyprus, Bulgaria, Greece, Latvia, and Italy. Indeed, high levels of NPLs weighed on banks' ability to lend as well as to invest which hence degraded its efficiency.
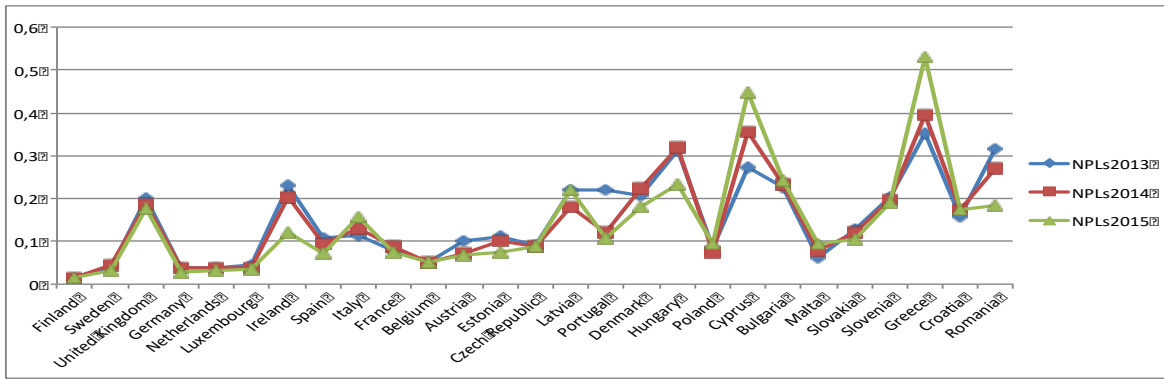
Fig 2:-Evolution of the NPLs per country over the period 2013-2015.

To gain further insights into the impact of a bank's location on its efficiency and following EBF Facts & Figures (2015), we proposed to classify the studied countries into four different geographical areas. This grouping was undertaken according to some previous studies as well as some adopted traditions and patterns (Table 6).
Fig 3 reveals that the average inefficiency scores had increased over time, suggesting the diffusion of inefficiency of European banks across all regions. Moreover, the Northern region seems to be somewhat more efficient followed by the Western European countries. In contrast, the Eastern region appears as the least efficient region advanced by the Southern one.

**Table 6:-**Classification of the countries in four main regions.

Region	Countries	Number of banks
Central-Eastern and Eastern European countries	Bulgaria, Czech Republic, Croatia, Estonia, Latvia, Hungary, Romania, Poland, Slovakia and Slovenia	106
Central-Western and Western European countries	Austria, France, Belgium, Germany, Luxembourg, Ireland, Netherlands and United Kingdom	176
Northern European countries	Denmark, Finland and Sweden	46
Southern European countries	Cyprus, Italy, Greece, Malta, Spain and Portugal	95

Fig 3 reveals that the average inefficiency scores had increased over time, suggesting the diffusion of inefficiency of European banks across all regions. Moreover, the Northern region seems to be somewhat more efficient followed by the Western European countries. In contrast, the Eastern region appears as the least efficient region advanced by the Southern one.

Based on Table 7, a deeper analysis demonstrated, from one hand, that the relatively less inefficiency of the Northern banks was due to the 26.7% Sweden efficient banks as well as to the fairly inefficiency level of the Finnish banks. Furthermore, in 2014 and 2015 the percentage of efficient Finnish banks increased to 20%. However, the score of the Western region owed to the moderately high percent of efficient Irish, Luxembourg, and English banks (28.6%, 28.6%, and 32.6% respectively). From the other hand, while the lowest efficiency scores of the Eastern region mainly originated from the weak efficiency of the Romanian, the Croatian, and the Slovenian banks, the feeble scores of the banks in Cyprus had marked the Southern region.

Furthermore, Table 8 reveals that, over all the period 2013-2015, the highest number of efficient banks was in the Western region. Nevertheless, the average inefficiency score of this region was higher than that of the banks in the Northern one. This may provide evidence that Northern banks compared to their counterparts had better converged during the studied period. In addition, Table 8 shows that the least number of efficient banks is situated in the Eastern region. This may as well justify the weak efficiency scores of the banks of this region besides the existence of the most inefficient countries in the region (Romania, Croatia, and Slovenia).
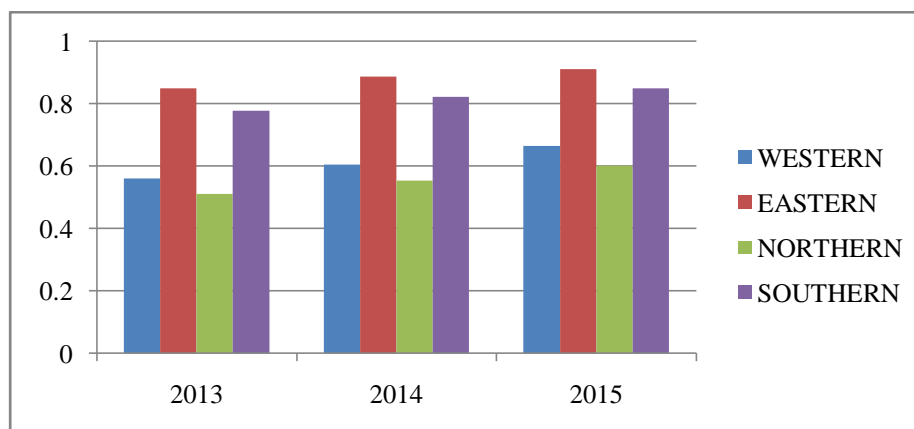
Figure 3:-Inefficiency evolution per region over 2013-2015.

Based on our findings, it seems that the European banking sector needs more challenging efforts in order to pin up recovery signs from the previous crises. Furthermore, the recovery economic sign perceived during the post-crises appears to be not complemented by a similar symptom at the banking sector efficiency level. Indeed, as displayed by Fig 4, in contrast to the revealed efficiency decrease, the European banks had generated a positive ROE and an apparent increase over the three years 2013, 2014 and 2015 after suffering from negative values during the years 2008, 2011 and 2012. Specifically, since 2013, the profitability had known a slight recovery with an average ROE of 2.2%, 4.8% and 6.5% on 2013, 2014 and 2015, respectively.

Table.7:-Percentage of efficient bank per country over time.

Countries	Number of banks	2013		2014		2015	
		Efficient bank	Percentage	Efficient bank	Percentage	Efficient bank	Percentage
Belgium	7	0	0	0	0	0	0
Croatia	12	0	0	0	0	0	0
Cyprus	7	0	0	0	0	0	0
Czech Republic	14	0	0	1	0,071	1	0,071
Estonia	4	0	0	0	0	0	0
Finland	5	0	0	1	0,2	1	0,2
Greece	6	0	0	0	0	0	0
Malta	3	0	0	0	0	0	0
Romania	11	0	0	0	0	0	0
Slovakia	9	0	0	0	0	0	0
Slovenia	8	0	0	0	0	0	0
Poland	21	1	0,048	1	0,048	1	0,048
Denmark	26	2	0,077	3	0,115	2	0,077
Bulgaria	11	1	0,091	1	0,091	1	0,091
Austria	9	1	0,111	0	0	0	0
Portugal	9	1	0,111	1	0,111	1	0,111
Spain	18	2	0,111	3	0,167	3	0,167
France	60	8	0,133	9	0,15	8	0,133
Italy	52	8	0,154	8	0,154	7	0,135
Germany	25	4	0,16	5	0,2	5	0,2
Hungary	6	1	0,1667	1	0,167	1	0,167
Latvia	10	2	0,2	0	0	0	0
Netherlands	12	3	0,25	1	0,083	1	0,083
Sweden	15	4	0,267	4	0,267	4	0,267
Ireland	7	2	0,286	2	0,286	2	0,286
Luxembourg	7	2	0,286	2	0,286	2	0,286

| United Kingdom | 49 | 16 | 0,326 | 18 | 0,367 | 16 | 0,326 |
| Total | 423 | 58 | | 61 | | 56 | |

Table 8:-Percentage of efficient bank per region over time.

	2013		2014		2015	
	Number	Percentage	Number	Percentage	Number	Percentage
Central-Western and Western countries	36	20,45	37	21,02	34	19,32
Central-Eastern and Eastern countries	5	4,72	4	3,77	4	3,77
Northern countries	6	13,04	8	17,39	7	15,22
Southern countries	11	11,58	12	12,63	11	11,58
Total	58	13,71	61	14,42	56	13,24
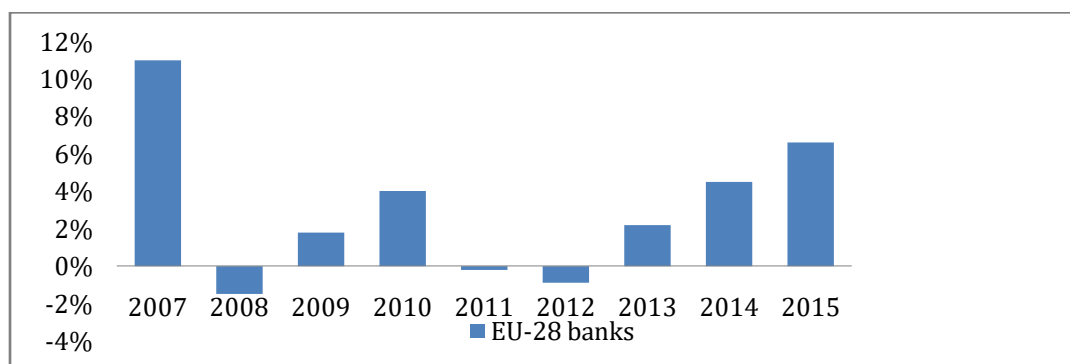
Fig 4: Evolution of the EU banking system ROE.

Conclusion:-

This paper provides a thorough analysis of the efficiency of European banking systems. It contributes to previous research on bank efficiency at many levels. To our knowledge, this is the first study in the banking context that considers simultaneously both non-discretionary and undesirable variables in the efficiency assessment. Nevertheless, treating fixed assets as non-discretionary inputs seems to not significantly affect the efficiency scores compared to the case where they are treated as discretionary. Furthermore, this study is among very few ones that introduce the NPLs as undesirable outputs in the efficiency assessment process. The obtained outcomes confirmed that ignoring them tends to overestimate the inefficiency scores.

Moreover, the results reveal an increasing level of the average inefficiency for most EU country as well as for the different EU regions. These outcomes may indicate the persistence of the impact of the financial crises and the inability of the European banking system to really recover from the crises. Furthermore, the apparent positive increase in the profitability of the European banks over the three years 2013, 2014 and 2015 seems to be an illusion due to inflation.

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