The Impact of Non-bank Lending on Bank Efficiency: Data Envelopment Analysis of European Banks

Galia Kondova and Trishit Bandyopadhyay

Abstract—**This paper applies a data envelopment analysis (DEA) to study the effect of non-bank financial intermediation on bank efficiency in the eight EU jurisdictions individually monitored under the Financial Stability Board (FSB) Global Shadow Banking Monitoring Report in the period 2014-2016. The efficiency analysis is conducted by applying a profit-based input-oriented DEA variable returns-to-scale model in a two-stage procedure. In the first stage, the average DEA efficiency scores are calculated. We find evidence that the average aggregate technical efficiency increased on average from 2014 to 2016. In the second stage, the impact of environmental factors like the Financial Stability Board's (FSB) narrow measure on non-bank financial intermediation as well as macroeconomic factors is analyzed by conducting a Tobit regression. The results provide evidence of a negative relationship between non-bank financial intermediation and average bank efficiency and a positive impact of GDP on average bank efficiency. These novel empirical findings contribute to the policy discussions on the effect of non-bank financial intermediation on bank performance and thus on financial stability. Moreover, our analysis provides unique initial evidence in favor of the hypothesis that increased non-bank financial intermediation might result into a reduction of bank profitability.**

Index Terms—**Bank efficiency, data envelopment analysis, financial stability, non-bank financial intermediation.**

I. INTRODUCTION

The European Banking Authority (EBA) states in its 2017 Risk Assessment Report on the risk and vulnerabilities in the European Union (EU) banking sector that "despite recent improvements, the persistent low profitability of EU banks remains a key concern" [1]. Thus, bank profitability is of special interest not only to shareholders but also to policy makers since it is an indicator of bank soundness and hence of banking sector stability. A stable banking sector in turn is important for capital allocation and economic growth [2].

Several papers have already studied the effect of low interest environment on bank profitability in advanced economies [3]-[5]. In general, these studies find out that over time low interest rates have a negative impact on bank profitability due to their negative effect on net interest margins. Reference [3] stresses out, however, the importance of controlling for the offsetting positive effect on profitability of increased economic activity due to low interest rates.

In addition to studying the monetary policy impact on bank profitability in the euro area, [3] provides evidence of "a positive and highly significant impact" of cost-efficiency on profitability. Moreover, the authors conclude "operational efficiency is a major avenue to explore in order to improve bank profitability".

This study aims to fill the research gap on operational efficiency in the EU banking sector by conducting a Data Envelopment Analysis (DEA) efficiency benchmarking among eight of the largest banking sectors in the EU, namely the United Kingdom, Luxembourg, Germany, Italy, France, Spain, the Netherlands and Belgium. The dataset used in the study covers financial data on all banks reported under the EBA's EU-wide transparency exercise for the above-mentioned countries and for the reporting period 2014-2016.

This study contributes to the existing bank efficiency literature in several ways.

This work is the first one (to the best knowledge of the authors) to study the post-crisis technical efficiency in the major European banking sectors by applying a Data Envelopment Analysis. Existing DEA analyses of EU banks have studied efficiency prior to the global financial crisis [6]. Moreover, these analyses have applied a different set of input and output variables.

The second innovation of this paper is that it is the first one to study the effect of non-bank financial intermediation[1] on bank efficiency in the EU. The studied eight banking sectors correspond to the eight EU jurisdictions individually monitored and reported in the FSB's 2017 Shadow Banking Report [7]. Research on the effect of non-bank lending on bank technical efficiency in the EU prior to this study was non-existent to the best of the authors' knowledge.

The existing literature on non-bank lending has studied aspects like its role in the recent financial crisis, the implications for financial stability, the social benefits of the sector, the associated challenges for financial supervision and regulation [8] as well as securitization and collateral intermediation in the non-bank financial sector [9]. In addition, [10] analyzes the interconnectedness between EU

[1]The term non-bank financial intermediation refers to the narrow measure of non-bank financial intermediation of the Financial Stability Board's Global Monitoring Report on Non-Bank Financial Intermediation (former Shadow Banking Report). A detailed description of the narrow measure is provided in Table II. Synonymous terms of non-bank financial intermediation used in the paper are "non-bank lending", "market-based finance" and "shadow banking" as previously used by the FSB in their monitoring reports.

banks and shadow banking entities. For the U.S. a recent study by [11] summarizes that "shadow bank market share in residential mortgage origination nearly doubled from 2007-2015, with particularly dramatic growth among online "fintech" lenders". The authors provide evidence that "regulation accounts for roughly 60% of shadow bank growth, while technology accounts for roughly 30%" [11].

Finally, this paper applies an innovative methodological approach by combining a profit-oriented DEA model of input and output variables following [12] in a two-stage procedure.

II. METHODOLOGY

A. Data Envelopment Analysis

The initial concept of DEA as a productivity and efficiency measurement tool is to be credited to the work of Farrell back in 1957 [13], which defined technical efficiency as the ability of a firm to obtain maximum feasible output from a given amount of inputs. Its application as a practical research tool though was facilitated by the development of the Charnes, Cooper and Rhodes (CCB) model and the one of Banker, Charnes and Cooper (BCC) [13].

The CCR model assumes constant returns-to-scale (CRS) of the production function. The objective score of the CCR model is designated technical efficiency (TE). On the other hand, the BCC model is built on the assumption of variable returns-to-scale (VRS). The objective value of the BCC model is said to reflect pure technical efficiency.

It argues that the CRS assumption is appropriate only in case all units are operating at an optimal scale [13]. In practice, there are usually factors such as imperfect competition, constraints to finance, etc. that lead to operation at suboptimal scale.

DEA uses a non-parametric mathematical linear programming approach. It gives a comparative ratio of weighted outputs to inputs for each decision-making unit (DMU). The relative score takes values between 0 and 1 (0 and 100%). A score of less than 1 indicates inefficiency relative to the units on the efficient frontier of best performers [7].

The DEA method estimates a comparative ratio of weighted outputs to inputs for each decision-making unit (DMU) in the sample [13]. The relative score takes values between 0 and 1 (0 and 100%). A score of less than one (respectively 100%) indicates inefficiency relative to the units on the efficient frontier of best performers [14].

DEA estimates a set of weights so that the ratio of weighted sums of the outputs and inputs as outlined in (1) is maximized for each unit.

$$E = \frac{\sum_j w_j Y_j}{\sum_i v_i X_i}$$

(1)

where E denotes the efficiency score, X_i denotes inputs, Y_j denotes outputs, w_j denotes the out-put weights to be estimated, v_i denotes the input weights to be estimated. DEA computes a separate set of weights for each bank, instead of using fixed weights for all units under evaluation. Weights are optimized to make each bank's score the best possible

under the constraint that no bank's efficiency exceeds one when using the same weights.

According to the model specification, it is possible to measure either input-oriented or output-oriented technical efficiency [15]. As explained by [16], the input-orientation implies keeping outputs fixed while exploring the proportional reduction in inputs. The output-orientation, on the other hand, explores the possible proportional increase of outputs while keeping inputs constant.

Considering the fact that there are factors that influence efficiency but are not direct inputs or outputs to the production process, the DEA-based efficiency analysis is expanded to incorporate the impact of these environmental factors. There are different approaches to study the impact of environmental factors. One method to incorporate the environmental factors in the efficiency analysis is to conduct a slacks-based DEA model combined with a Tobit regression. In particular, the input slacks (non-radial input savings) from a DEA model are obtained first. These are then regressed on a set of external factors that are likely to affect efficiency. The estimated difference in the predicted slacks is then used to adjust the inputs in the DEA model. Finally, the DEA model is re-estimated using the adjusted inputs and the original output measures [12].

Reference [17] presents an alternative approach whereby the environmental variables are included within the constraints of the DEA model. In particular, [17] includes the nondiscretionary (environmental) variables "within the constraints but not in the objective function of the DEA model". Thus, the environmental factors are incorporated directly in the DEA model.

B. First-Stage DEA Input-Oriented BCC Profit-Based Model

In this study, we use a profit-based input-oriented variable returns to scale DEA model. This model specification has been identified as the most appropriate one considering the recognized significant impact of cost efficiency on profitability [3]. Following [12], we identify revenue components from the profit and loss statements (P&Ls) as outputs and cost components from the P&Ls as inputs in our model. The concrete input and output variables are outlined in Table I.

TABLE I: INPUT AND OUTPUT VARIABLES

Input Variables	Output Variables
Administrative Expenses (AdminExp)	Net Interest Income (NetIntInc)
Depreciation (Deprn)	Net Fee and Commission Income (NetFee)
Loan Loss Provisions (Prov)	

The input variables comprise of Administrative Expenses, Depreciation and Loan Loss Provisions. The non-interest operating expenses measured by the variable Administrative Expenses are the major cost factor on the bank's P&L. Depreciation is also a cost factor to be taken into consideration. The Loan Loss Provisions is a particularly important cost factor because it controls for the risk and the loan quality [18].

The output variables are the Net Interest Income and the Net Fee and Commission Income from the revenue components of the bank P&Ls.

C. Second-Stage Tobit Regressional Analysis of Environmental Factors

The bank-external factors, the environmental variables, that might influence the efficiency and are not included as inputs are studied by a Tobit regressional analysis. Taking into consideration the findings of relevant empirical studies like the one of [12], we use the following macroeconomic variables per country as environmental variables in our model, namely annual GDP, Government Consumption, Household Consumption, Wages, Unemployment rate, House Price Index and EMU Bond Yields. In addition to these macroeconomic variables, we include the "narrow" shadow banking measure as reported by the FSB in its Global Shadow Banking Reports 2017 [7]. Table II provides an overview of the environmental variables and their abbreviation used in the second stage of the regression. We conduct a Tobit regressional analysis.

TABLE II: ENVIRONMENTAL VARIABLES

Non-Bank Financial Intermediation (Shadow Banking)
FSB measure that includes the following 5 economic functions (EF): EF1: management of collective investment vehicles (CIVs); EF2: entities engaged in loan provision which depends on short-term funding. Consumer finance, commercial property finance and equipment finance are among the various activities captured; EF3: intermediation of market activities which depends on short-term funding and includes i.a. secured funding of client assets and securities borrowing and lending. Broker dealers/ investment firms are the main representatives of this category; EF4: entities facilitating the creation of credit such as financial guarantors; EF5: securitisation-based provision of funding to banks and/or non-bank financial entities, with or without the transfer of assets and risks from banks and/or non-bank financial entities, in million Euro.
GDP (GDP)
Eurostat gross domestic product in million Euro.
Unemployment rate (Unempl)
Eurostat Annual rate of average unemployment in % of active population.
House Price Index (HausPindex)
Eurostat Annual rate of change (2015=100)
EMU Bond Yields (EMUbondY)
Eurostat EMU convergence criterion bond yields, annual data in %.

III. DATA

The studied eight banking sectors correspond to the eight EU jurisdictions monitored under the Financial Stability Board (FSB) Global Shadow Banking Monitoring Report in the period 2014-2016. These eight EU countries are also the ones with the largest shadow banking sectors as reported by the Financial Stability Board [7].

The dataset comprises of 72 banks from eight European Union countries, namely 4 from the United Kingdom (UK), 2 from Luxembourg (LU), 16 from Germany (DE), 15 from Italy (IT), 10 from France (FR), 14 from Spain (ES), 5 from the Netherlands (NL) and 6 from Belgium (BE) that report under the EU-wide transparency exercise of the EBA since 2014. Thus the timeline of the studied period comprises three years, namely 2014–2016. The number of the reporting banks in 2014 accounted to 66, in 2015 to 72, and in 2016 to 67. The majority of the banks in the EU-wide transparency exercise comprises of the so-called Global Systemically Important Institutions (G-SIIs) as well as other large institutions with an overall exposure measure of more than EUR 200 billion Euro.

Furthermore, the data on the macroeconomic environmental variables comes from Eurostat and the data on the shadow banking variable comes from the FSB's Global Shadow Banking Monitoring Report 2017 [7]. Table III provides an overview of the descriptive statistics of all the variables for the 205 banks in the sample for the period 2014-2016. The numbers are in million Euro.

TABLE III: DESCRIPTIVE STATISTICS – INPUT AND OUTPUT VARIABLES (IN MILLION EURO)

	AdminExp	Deprn	ProvPlsMns	NetIntInc	NetFee	
Max	30'585	3'385	3'961	32'477	14'592	
Mean	4'683	429	377	4'575	2'245	2014
Min	54	1	0	77	0	
Stdev	7'067	716	900	6'863	3'561	
Max	33'908	3'567	6'373	33'761	15'403	
Mean	4'567	425	441	4'380	2'176	2015
Min	59	2	0	51	0	
Stdev	7'421	762	1'305	7'094	3'619	
Max	30'951	3'846	8'424	31'227	12'995	
Mean	4'702	419	403	4'396	2'171	2016
Min	60	2	0	56	0	
Stdev	7'102	721	1'159	6'623	3'384	

Moreover, a summary statistics of the environmental variables and their abbreviations is presented in Table IV.

TABLE IV: DESCRIPTIVE STATISTICS – ENVIRONMENTAL VARIABLES (IN MILLION EURO)

	ShadowBank	GDP	Gcons	Hcons	Wages	Unempl	HausPindex	EMUbondY
Max	2'921'940	3'159'750	615'494	1'624'208	1'309'319	24.50	8.50	2.89
Mean	1'013'150	1'445'273	297'164	797'014	550'306	9.46	3.00	1.22
Min	113'876	49'993	8'350	14'419	20'417	4.10	-4.90	0.09
Stdev	836'415	1'014'966	201'628	575'162	416'420	5.49	3.39	0.76

TABLE V: AVERAGE BANKING SECTOR DEA EFFICIENCY SCORES PER COUNTRY AND YEAR

	Yearwise Average Efficiencies of Countries							
	BE	DE	ES	FR	UK	IT	LU	NL
2014	0.592	0.793	0.804	0.883	0.827	0.738	0.670	0.950
2015	0.698	0.810	0.748	0.858	0.830	0.660	0.594	0.929
2016	0.745	0.813	0.740	0.916	0.900	0.680	0.665	0.955

IV. RESULTS

A. First-Stage DEA Input-Oriented BCC Profit-Based Model

In the first stage of the analysis, we estimate the DEA technical efficiency scores based on the defined input-oriented profit-based BCC DEA Model. Table V presents the DEA average efficiency scores for the selected eight banking sector over the studied period of time. It could be seen from Table V that the average efficiency over the three studied years has been higher in countries like the

Netherlands, the UK, Germany, and France as compared to the rest of the countries. The aggregate average efficiency for all the studied banking sectors as could be seen from Table VI has slightly increased from 2014 to 2016 after recovering from a slight deterioration in 2015.

TABLE VI: Aggregate Average DEA Efficiency Scores per Year

	2014	2015	2016
Max	1.000	1.000	1.000
Mean	0.782	0.766	0.802
Min	0.176	0.186	0.270
Stdev	0.212	0.211	0.206

B. Second-Stage Tobit Regressional Analysis of Environmental

In the second stage of the analysis, we study the effect of the identified environmental variables on the average country efficiency scores for the three year period (a total of 24 observations) by conducting a Tobit regressional analysis. The regression results are outlined in Table VII.

TABLE VII: Tobit Regression Results

Efficiency	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
ShadowBank	-5.00e-08	2.70e-08	-1.85	0.080	-1.07e-07	6.56e-09
GDP	4.40e-08	1.90e-08	2.32	0.032	4.27e-09	8.37e-08
Unempl	-.002031	.004472	-0.45	0.655	-.011391	.007329
HausPindex	.0069651	.0064697	1.08	0.295	-.0065761	.0205063
EMUbondY	-.0181372	.0311644	-0.58	0.567	-.0833651	.0470908
_cons	.7906523	.0723096	10.93	0.000	.6393064	.9419981
/sigma	.0888728	.0128272			.0620251	.1157204

TABLE VIII: Non-Bank Financial Intermediation (Shadow Banking) in Million Euro (FSB Narrow Measure)

	2014	2015	2016
DE	1'380'954	1'470'378	1'540'530
FR	1'183'663	1'217'762	1'241'910
UK	1'397'139	1'329'328	1'316'250
BE	113'876	136'409	120'960
ES	266'181	274'911	275'310
IT	450'856	456'638	439'020
LU	2'518'635	2'821'000	2'921'940
NL	490'530	485'394	466'020

Despite the relatively small sample of observations, one variable, namely the Shadow Banking is found negatively significant with a p-value of 0.08. Considering the input-oriented (cost-oriented) optimization specification of our model, the negative correlation between shadow banking activity and efficiency could be explained with an increase in the loan loss provisions on the cost side of the model due to more risk-taking.

At the same time, our analysis provides evidence of a positive statistically significant impact of the GDP variable on average efficiency in the studied countries with a p-value of 0.03.

It is also worth noting that although shadow banking is found to be negatively related to average technical efficiency, it has higher volumes in the countries with higher average bank efficiencies. The legal environment could be an important explanatory factor for this relationship that is to be included in the future research agenda.

V. Conclusion

This paper studies bank efficiency developments in the eight EU countries individually monitored under the FSB Global Shadow Banking Report 2017, namely, France, Germany, Belgium, the Netherlands, Italy, Spain, Luxembourg and the UK [7]. The dataset comprises of 72 banks from the above-mentioned eight European Union countries that are part of the EU-wide transparency exercise of the European Banking Authority for the period 2014-2016. The paper applies the profit-based input-oriented variable return-to-scale production DEA model in a two-stage procedure. The model input variables are administrative expenses, depreciation, and loan loss provisions. The net interest income and net fee and commission income are the model outputs.

In the first stage, the average DEA efficiency scores were calculated. We find evidence that the average aggregate technical efficiency slightly increased from 2014 to 2016. In the second stage, the impact of environmental factors like non-bank financial intermediation (shadow banking) and macroeconomic factors was analyzed by conducting a Tobit regression. The results provide evidence of a negative relationship between shadow banking and technical efficiency and of a positive impact of the GDP variable on average efficiency scores. Thus our analysis provides unique initial evidence in favor of the hypothesis that increasing non-bank financial intermediation has a negative impact on bank profit efficiency as discussed in the FSB Report on Fintech Credit [19]. It is worth noting though that countries with large non-bank financial intermediation sectors like the UK, France and Germany (see Table VIII) also demonstrate higher average technical efficiency scores as compared to the rest in the sample.

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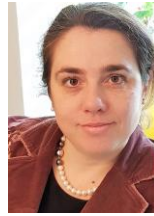
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