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Bootstrapping efficiency scores of microfinance institutions in West African economic and monetary union

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Abstract

We used a Data Envelopment Analysis bootstrap approach to compute the efficiency scores of Microfinance Institutions in the West African Economic and Monetary Union (WAEMU). Our results indicate that our efficiency scores are much lower than the original DEA scores. Indeed, the MFIs had an average score of 63.61%, suggesting that efficiency could be improved by 36.39%. There were also significant efficiency disparities among WAEMU member states, with the maximum value in Burkina Faso at 71.51% and the minimum value in Benin at 52.04%. The sizes of these MFIs did not seem to impact their efficiency levels. However, the ages of these MFIs did impact their efficiency levels: MFIs with less than 10 years of experience displayed the highest levels of efficiency. Additionally, the type of MFI also impacted efficiency levels: credit unions were the most efficient followed by Non-Governmental Organizations and then Non-Bank Financial Institutions.

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BOOTSTRAPPING EFFICIENCY SCORES OF MICROFINANCE INSTITUTIONS IN WEST AFRICAN ECONOMIC AND MONETARY UNION (WAEMU)

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Abstract

We use DEA Bootstrap to compute efficiency scores of MFIs in West African Economic and Monetary Union (WAEMU). Our results show that the efficiency scores are much lower than the original DEA. Indeed, MFIs have a score of 63.61%, suggesting that efficiency could be improved by 36.39%. There are huge disparities among WAEMU member states with the maximum for Burkina Faso at 71.51% and the minimum for Benin at 52.04%. Also, the size of MFIs doesn't seem to make a difference in the level of efficiency. By cons, the age does play a role, with MFIs of less than 10 years of experience displaying the highest level of efficiency. As for the type, credit unions are the most efficient one before NGOs and NBFIs.

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1. Introduction

Micro-finance institutions (MFIs) and their levels of efficiency have been the subject of many studies. Indeed, many economists have questioned how efficiency can be measured given the dual roles of these institutions: they have both social and financial roles (Bassem, 2008; Haq et al., 2009; Qayyum, 2006; Varman, 2008; Soulama, 2005, 2008). Initially, studies were only interested in financial efficiency. However, these studies were quickly criticized by authors like Gutiérrez-Nieto et al. (2007, 2009). Critics emphasized the need to incorporate social roles in measurements of MFI efficiency. Indeed, MFIs are financial institutions that lend money to people who have generally been excluded from traditional financial systems like banks. Therefore, their target customers are among the most impoverished people, meaning individuals who are unable to provide collateral for loans.

Hermes et al. (2011) claim that the MFIs mission is not only to provide financial intermediation, similar to what is offered by banks, but also to provide outreach. There are two opposing economic schools with differing opinions about the role of outreach and the role of financial sustainability in achieving the goals of MFIs. Specifically, welfarists identify outreach goals as the dominant priority (Hashemi and Rosenberg, 2006; Montgomery and Weiss, 2005; Woller, 2002), whereas institutionalists identify sustainability and efficiency as the dominant priorities (Christen, 2001; Isern and Porteous, 2005; Rhyne, 1998). The outreach view highlights the importance of using MFIs to provide credit to impoverished individuals who have no access to commercial banks; their aim is to reduce poverty and help the poor to establish their own income-generating businesses. On the contrary, institutionalists highlight the importance of MFIs' financial sustainability. This means that MFIs should be able to cover the cost of lending money to their customers. This might imply that they must lend to more financially reliable and less impoverished clients.

These two views may potentially conflict. Indeed, recent developments in the MFIs reveal tough competition in this sector. Commercialization and the use of new technologies lead to costs increases in the MFIs' lending activities (Rhyne and Otero, 2006; Kapoor et al., 2007, Hartarska and Nadolnyak, 2007). Those increased costs may lead MFIs to transition from serving the most impoverished individuals to serving more viable clients. Reaching the poor and providing them with credit may be very costly. In addition, small loans are accompanied with high transaction costs, due to the screening, monitoring, and administration costs incurred per loan. Thus, the unit transaction costs for small loans are higher than the unit transaction costs for larger loans (Lapenu and Zeller, 2002; Paxton and Cuevas, 2002). However, Hermes et al., (2011) have shown that financial sustainability may help to support the outreach goals of MFIs. Indeed, sustainable MFIs may increase the financial amount of the loans given to impoverished individuals and help to ensure that loans are given over a longer period of time. The latter view tends to reconcile MFIs' goals in both outreach and financial sustainability. Therefore, in our study, we estimated a Data Envelopment Analysis (DEA) index encompassing financial sustainability and outreach—both goals that are important to MFIs will be highlighted. We will additionally apply the DEA bootstrap approach in our research.

Gutiérrez et al. (2007, 2009) used a DEA in their studies. This nonparametric method measures an efficiency score compared to a so-called efficient frontier. It is composed of the most efficient MFIs. Being non-parametric, this method does not take into account measurement errors and therefore leads to an over-estimation of efficiency. This weakness was identified by Simar and Wilson (1998, 2002), who sought to correct this error through a bootstrap approach. Thus, the DEA bootstrap approach allows for the replication of the sample to calculate the efficiency scores. This will provide more refined measurements, and the accuracy will be indicated by a confidence interval. This method was applied to several economic entities, including banks, hospitals, and various industries (Staat, 2006; Halkos and Tzeremes, 2010); however, it has only been applied to MFIs in a few studies.

In this article, we propose to measure MFIs' efficiency in the West African Economic and Monetary Union (WAEMU)[1] using the DEA bootstrap approach. This study is relevant because it allows us to measure the efficiency of MFIs after restructuring reforms were implemented in this area. Years ago, this sector suffered from various failures, such as mismanagement, a lack of capability, and a lack of financial monitoring. Thus, several restructuring programs were developed whereby MFIs no longer had informal frameworks for their activities but were subject to regulation instead. Specifically, these regulations intended to frame the industry by defining the scope of microfinance activities and frameworks. Microfinance regulations also aimed to provide oversight and monitoring by implementing prudential standards. To this end, MFIs are subject to particular methods of accounting and provisioning for nonperforming loans. They are also subject to specific financial ratios and prudential management to avert potential crises in the industry and to ensure that depositors are protected.

Measuring MFIs' efficiency in the WAEMU after these reforms using the DEA bootstrap approach allows us to obtain more accurate measures of efficiency (Löthgren, 1998). We will be able to identify the levels of efficiency achieved after these restructuring reforms were implemented and assess whether there is still work to be done to increase MFIs' efficiency even more. Our study will uniquely contribute to existing literature on MFI efficiency measurements because this method has rarely been used in examining those institutions. As a second contribution, this study will reveal MFI efficiency in the WAEMU since the implementation of the reform programs. The findings will indicate whether or not MFI efficiency improved in the WAEMU after the reforms.

This paper is organized as follows: Section 2 presents the DEA bootstrap method and the data used. Section 3 comments on the results of our estimates. Finally, section 4 provides some concluding remarks.

2. Methodology

As mentioned in the introduction, the DEA method measures the efficiencies of firms by building an efficient production possibility frontier using inputs and outputs. The inefficiency score is calculated as a deviation from the optimal frontier. Charnes et al. (978) were the first to introduce the DEA method to firm management. In their model, there was an assumption of constant returns to scale (CRS), which means that proportional increases of input lead to proportional increases in output. This assumption is valid when firms operate at an optimal level. However, this is not always the case. Therefore, Fare et al. (1983) and Banker et al. (1984) introduced the variable returns to scale (VRS). The latter is more suited to imperfect competition in a sector and to the existence of certain levels of heterogeneity between firms (Assaf and Matawie, 2010).

[1] The WAEMU is an economic and monetary union that is comprised of the following countries: Benin, Burkina Faso, the Ivory Coast, Bissau-Guinea, Mali, Niger, Senegal, and Togo.

We use the VRS assumption since it better suits the case of MFIs. Indeed, the CRS assumption is appropriate when all Decisions Making Units (DMU) are operating on an optimal scale. This is not the case for MFIs because they are financial institutions with a specific statute. The environment in which they evolve is characterized by imperfect competition, constraints on finance, and so forth. This means that they may not operate at optimal levels. When not all DMU's are operating at an optimal scale, using CRS specifications will measure technical efficiencies being confounded by scale efficiencies. Therefore, Banker et al. (1984) suggested using VRS specifications, which allows for the calculation of technical efficiency devoid of scale efficiency effects. In the same vein, Berg et al. (1993) used the DEA method by setting VRS and CRS hypotheses. As previously stated, VRS hypotheses account for economies of scale in the industry, as well as imperfect competition and prudential regulation. Therefore, VRS provides more robust efficiency scores due to by accounting for misspecifications. However, with this specification, large DMUs may artificially seem more efficient because of the scale effect. In turn, CRS prevents this measurement error because it allows for comparisons between small banks and large banks without misincorporating the scale effect. Thus, to provide a fair interpretation, the authors will produce results that are shared by both assumptions. Therefore, we will follow the abovementioned reasoning.

The second specification that we have to establish is the result of a choice: choosing between an input-orientated DEA and an output-orientated DEA. The first choice provides an indication of how inputs can be reduced while maintaining constant levels of output, while the second choice provides an indication of how much output can be increased while keeping constant levels of input (Coelli et al., 1998). We opted for an input-oriented efficiency measurement because MFIs' first aim is to fight poverty by distributing credit to people who are excluded from the banking system. The linear programming problem is as follows:

$$\min_{\theta,\lambda} \theta_i \tag{1}$$

$$\begin{aligned} S.t. -y_i + Y\lambda &\geq 0 \\ \theta x_i - X\lambda &\geq 0 \\ I1\lambda &= 1 \\ \lambda &\geq 0 \end{aligned}$$

In this equation, y_i is the M*1 vector of the observed outputs of the form I, x_i is the vector N*1 of observed inputs, θ_i is a scalar that represents the technical efficiency score of the i-th firm, and λ is a I*1 vector of constants.

However, the main limitation of the DEA is that it does not deal with noise or random errors. Therefore, it does not accurately determine the efficiency scores because they are not estimated but statistically calculated using linear programming. Simar and Wilson (1998, 2000) addressed these shortcomings by using a bootstrap approach. This approach consists of randomly selecting thousands of pseudo-samples, starting with the observed sample. Those thousands of pseudo-estimates form an empirical distribution of the efficiency score. This distribution is subsequently used as an approximation of the true distribution of the efficiency score. For details about the different steps, the reader can refer to Simar and Wilson (2000).

Berger and Humphrey (1997) pinpointed the sensitivity of the results concerning the choice of inputs and outputs. Recently, Serrano-Cinca and Mar Molinero (2004) and Gutiérez-Nieto et al. (2009) used the principal component analysis method to explore how different choices of inputs and outputs impact the measurement of MFI efficiency. Following these authors, we chose the same inputs and outputs that are consistent with the production approach, which determines how the financial institution produces transaction and information services. In addition, our choice of inputs and outputs are also constrained by data availability. We chose three inputs, as described below. The first input is operational expenditures (FIEXP); it consists of interest payments on deposits, MFIs borrowings, and other financial charges. The second input is capital (CAP), as measured by equity. We then considered as third input, the number of MFIs' workers (PERS). We did not consider physical capital due to data limitations. We selected three outputs, as described below. The first output is a gross loan portfolio (GLP), and it reflects the role of financial intermediation. The second output is a return on assets (ROA), and it is used to take into account the financial management of the MFI. The third output is a poverty index (POV), which was calculated using the following formula:

$$POV = 1 - \frac{\frac{ALB}{GNIc} - \min\left(\frac{ALB}{GNIc}\right)}{Max\left(\frac{ALB}{GNIc}\right) - \min\left(\frac{ALB}{GNIc}\right)} \qquad (2)$$

Hermes et al. (2011) used the average loan per borrower (ALB) because it includes the idea that MFIs lend to impoverished individuals. The lower the indicator, the more impoverished the individuals covered by the MFI. Clearly, MFIs participate in financing the impoverished and alleviating poverty. To take into account differences in living standards, we divided the ALB by the Gross National Income per capita (GNIc). Thus, the closer the POV is to 1, the more the MFI lends to impoverished people, and the opposite effect is observed as the index approaches 0. Again, all variables expressed in monetary units were deflated by the consumer price index. Data were extracted from Mixmarket, which computes data from microfinance institutions worldwide. Ratios and variables in particular were calculated using balance sheets and financial statements from the MFIs. We used the most recent year with the most data concerning MFIs in the WAEMU, which was 2009.

3. Results

Like Berg et al. (1993), we estimated efficiency scores using the CRS and the VRS hypotheses. However, we based our comments on the results of the VRS hypothesis because it has the most relevant assumption in the case of MFIs. Table 4 in the appendix presents estimates of efficiency scores under the CRS hypothesis, while table 1 presents the estimates of efficiency scores using the DEA bootstrap method of Simar and Wilson (2000) under the VRS hypothesis. The first column presents MFIs, and the second column presents the original DEA scores that were computed using linear programming. Then, the table displays the bias of the DEA efficiency indicators as well as the median and the mean for the bootstrapped estimates for each MFI. The bootstrap technique is used to draw inferences, and the confidence interval bounds are provided to complete the table.

Results from the original DEA indicate an average efficiency score of 76.87% for the whole WAEMU zone. This means that MFIs could improve their efficiency by approximately 23%. However, there is a disparity in the results, among WAEMU members' countries—the maximum efficiency occurs in Burkina Faso with 90.31% and the minimum efficiency occurs in Benin with 55.98%. As we explained in the methodology section, the original DEA method is subject to statistical limitations and may not produce to accurate efficiency estimates.

Table I. Estimates of VRS efficiency scores using the DEA bootstrap method of Simar and Wilson (2000).

DMU	Score(Original)	Bias	Mean	Median	SD	Lower Bound	Upper Bound
01	0,6316	0,1438	0,5605	0,5921	0,0645	0,4261	0,6272
02	0,4262	0,0617	0,4046	0,4162	0,0308	0,3106	0,4240
03	0,6791	0,0882	0,6272	0,6410	0,0425	0,5159	0,6737
04	0,5120	0,0507	0,4886	0,4960	0,0232	0,4149	0,5087
05	0,4428	0,0357	0,4277	0,4289	0,0090	0,4079	0,4406
06	0,6673	0,0940	0,6136	0,6303	0,0450	0,5058	0,6619
07	1,0000	0,4136	0,7687	0,8699	0,1983	0,3998	0,9888
08	1,0000	0,5307	0,7380	0,8071	0,2213	0,2978	0,9878
09	1,0000	0,4287	0,7660	0,8752	0,2046	0,3882	0,9891
10	0,5047	0,0733	0,4728	0,4847	0,0326	0,3894	0,5055
11	1,0000	0,4844	0,7526	0,8600	0,2157	0,3435	0,9879
12	0,9139	0,1774	0,7924	0,8352	0,1050	0,5582	0,9043
13	1,0000	0,4642	0,7563	0,8563	0,2107	0,3671	0,9893
14	1,0000	0,3945	0,7672	0,7944	0,1861	0,4440	0,9888
15	1,0000	0,2608	0,8155	0,8194	0,1328	0,6003	0,9882
16	0,2598	0,0424	0,2511	0,2604	0,0202	0,1948	0,2703
17	1,0000	0,5141	0,7461	0,8343	0,2201	0,2968	0,9868
18	0,4044	0,0226	0,3955	0,3964	0,0048	0,3829	0,4024
19	0,5315	0,0620	0,5022	0,5127	0,0282	0,4235	0,5284
20	0,5200	0,0233	0,5082	0,5089	0,0054	0,4958	0,5168
21	0,6430	0,1475	0,5677	0,5909	0,0617	0,4337	0,6378
22	0,6104	0,0631	0,5758	0,5869	0,0296	0,5002	0,6062
23	1,0000	0,5195	0,7432	0,8330	0,2216	0,2980	0,9866
24	1,0000	0,5128	0,7441	0,8202	0,2192	0,3009	0,9883
25	1,0000	0,4849	0,7524	0,8499	0,2148	0,3431	0,9860
26	0,6438	0,0892	0,5933	0,6003	0,0356	0,5066	0,6388
27	1,0000	0,2785	0,8167	0,8249	0,1505	0,4702	0,9876
28	1,0000	0,5283	0,7381	0,7766	0,2216	0,3181	0,9886
29	1,0000	0,4751	0,7564	0,8537	0,2148	0,3529	0,9884
30	1,0000	0,4777	0,7567	0,8673	0,2158	0,3461	0,9888
31	1,0000	0,2684	0,8144	0,8450	0,1397	0,5539	0,9872
32	1,0000	0,4974	0,7469	0,8048	0,2143	0,3001	0,9897
33	0,3644	0,0357	0,3521	0,3550	0,0098	0,3270	0,3629
34	0,7788	0,1669	0,6841	0,7216	0,0943	0,4368	0,7714
35	0,6692	0,0901	0,6163	0,6244	0,0373	0,5284	0,6635
36	0,4990	0,0605	0,4723	0,4839	0,0274	0,3984	0,4961
37	0,7026	0,2215	0,5945	0,6428	0,0985	0,3761	0,6966
38	1,0000	0,3105	0,8040	0,8495	0,1640	0,4484	0,9876
39	0,3418	0,0735	0,3209	0,3318	0,0263	0,2524	0,3470
40	1,0000	0,2416	0,8403	0,9086	0,1498	0,4857	0,9882

However, the bootstrap approach discussed earlier will correct this problem. Due to the overestimation of the original method and the correction made in the confidence intervals, the original efficiency scores are not included in the confidence interval; rather, they are close to the upper bound of the confidence interval (Wijesiri et al., 2015). With the bootstrap correction, the average efficiency in the WAEMU zone is lower at 63.61%. This means that the efficiency could be improved by 36.39%.

This finding means that MFIs must make more substantial efforts then previously indicated by the results of the original DEA method. Again, Burkina Faso displayed the highest efficiency scores at 71.51%, while Benin displayed the lowest efficiency scores at 52.04%. After Burkina Faso, the following countries have the highest average bootstrap efficiency scores: Niger 70.5%, Senegal 68.31%, and the Ivory Coast 64.75%. The microfinance sectors in those countries were strongly restructured as part of the restructuring program, including merging some large networks and the foreclosures small savings and credit mutual funds cooperative groups and within other saving and credit institutions. From 2004 to 2006, Niger's and Senegal's numbers of MFIs decreased by 50% and 41%, respectively. This indicates that countries with sustained restructuring programs tend to perform better. The least efficient MFIs were closed, leaving only the most efficient institutions. As lower performing MFIs closed, the whole efficiency of the country improved. However, the maximum and minimum levels of efficiency were always realized by the same countries, with the respective values of 71.51% and 52.04%. The results from Benin and Burkina Faso may be explained by the fact that among the WAEMU countries, the number of MFIs in Benin declined dramatically during the restructuring period, while the number of MFIs in Burkina Faso only decreased slightly during this time. Such changes may indicate positive or negative performances within the MFIs in those countries, with MFIs having poor performance potentially leaving the market. From 2004 to 2006, in Benin, 65% of MFIs left the market, while in Burkina Faso, 7% of MFIs left the market. The central bank (Banque Centrale des Etats de l'Afrique de l'Ouest_BCEAO)'s report from 2006 explained this reduction by pointing to the consequences of the restructuring program, such as mergers within large networks and the foreclosures of small savings and credit mutual fund cooperative groups as well as other savings and credit institutions (BCEAO, 2006). These bankruptcies may explain the lower efficiencies of some MFIs, whose poor performance meant that they failed to meet market requirements.

For deeper analysis, we synthesized our estimated results and took into account the following characteristics of MFIs: the size, type, and number of years of experience (age). Concerning size, large MFIs are those with total assets higher than the sample average, of which there are eight institutions. Concerning type, there are three possible options: MFIs may be subsidiaries of NGOs, cooperatives, or non-bank financial institutions (NBFI). Finally, concerning years of experience, MFIs that have been operating for more than ten years are considered the most experienced in the business; they are sufficiently mature and therefore classified as experienced. We relied on the bootstrap scores for analysis purposes. Table 3 shows that size differences do not really explain differences in efficiency scores. Whether MFIs are large or small, the average efficiency score is approximately 63%. On the contrary, the other two characteristics seemed to impact efficiency levels. In particular, the highest levels of efficiency are found in MFIs that are cooperatives at 66%, followed by NGOs at 62.07%, and then non-bank financial institutions (NBFIs) at 61%. The NBFIs may have low scores because we incorporated MFIs' social (outreach) roles, which are not valued by financial institutions. Indeed, MFIs that are not NBFIs operate like financial institutions: they have more financial performance goals, and fulfilling social roles is a secondary aim. As for the MFIs related to NGOs, they are more prone to engage in financial service distribution to impoverished individuals, and financial performance is a secondary aim. In their development, NGOs often aim to fight poverty. Therefore, those NGOs tend to give grants to their subsidiaries. Therefore, those latter won't make many efforts for financial performance.

Our results are corroborated by the findings of Wijesiri et al. (2015) and Gutierrez-Niéto et al. (2009), who pinpointed the importance of social efficiency in NGOs. Lastly, credit unions connect social performance and financial performance most effectively in their activities, as their average efficiency scores are the highest when combining social and financial characteristics. Against all odds, the least experienced MFIs are the most efficient with an average score of 66.89% compared to the average score of 63.04% for more experienced institutions. Wijesiri et al. (2015) found that in a sample of 36 MFIs in Sri Lanka, mature MFIs were more financially efficient than less mature MFIs. Concerning social efficiency, those same matured MFIs were less efficient. Wijesiri et al. (2015) addressed this finding using the phenomenon of mission drift, as explained by Mersland and Strom (2010).

Table II. Average of the estimates of efficiency scores according to the WAEMU member countries

Countries	Score (Original)	Bias	Mean	Median	SD	Lower Bound	Upper Bound
Benin	0,5598	0,0790	0,5204	0,5341	0,0358	0,4302	0,5560
Burkina Faso	0,9031	0,3513	0,7151	0,7887	0,1629	0,3962	0,8939
Ivory Coast	0,8150	0,2905	0,6475	0,6826	0,1375	0,4015	0,8092
Mali	0,7455	0,2611	0,6150	0,6592	0,1117	0,3861	0,7377
Niger	0,8219	0,1838	0,7050	0,7126	0,0930	0,4884	0,8132
Senegal	0,8516	0,3175	0,6831	0,7310	0,1434	0,3954	0,8426
Togo	0,7087	0,1815	0,6064	0,6433	0,0932	0,3922	0,7031
WAEMU	0,7687	0,2477	0,6361	0,6773	0,1137	0,4035	0,7614

According to Mersland and Strom (2010), as MFIs mature, they tend to target safer customers that are therefore less vulnerable and less impoverished. Our efficiency score was calculated using social and financial characteristics of MFIs. Our results indicate that when considering these two aspects, the more experienced MFIs tend to be less efficient. This means that the issue of mission drift was verified, even when we considered the two aspects of MFIs' efficiency. Our results may be explained by the fact that although the mature MFIs have much more experience, they ensure their sustainability by emphasizing financial performance rather than social improvement. Hermes et al. (2009) indicate that MFIs tend to make trade-offs between outreach and efficiency to be sustainable. They pinpoint the fact that sustainable MFIs are those that are financially viable. And their financial viability is fulfilled at the expense of outreach. Our results are also corroborated by Wijesiri and Meoli (2015). They determined that in a sample of 20 MFIs in Kenya, mature MFIs tended to have lower efficiencies. They explained their results by indicating that mature MFIs become less able to respond to new challenges, they succumb to dynamic, younger MFIs, and they may also become less efficient (Barron et al., 1994).

Table III. Average estimates of efficiency according to MFIs' features

	DMU	Score (Original)	Bias	Mean	Median	SD	Lower Bound	Upper Bound
Size	Large	0,7648	0,2613	0,6325	0,6798	0,1184	0,3838	0,7574
	Small	0,7741	0,2476	0,6395	0,6794	0,114	0,4079	0,7668
Type	NGO	0,7431	0,2362	0,6207	0,6647	0,1068	0,3948	0,7363
	Credit Union / Cooperative	0,8048	0,2652	0,6599	0,7029	0,1238	0,4107	0,7969
	NBFI	0,7521	0,2799	0,61	0,6547	0,1194	0,3746	0,7447
Age	>10 years	0,7563	0,235	0,6304	0,6667	0,1082	0,4023	0,7493
	< 10 years	0,8309	0,302	0,6689	0,7271	0,1377	0,4083	0,8223

4. Conclusion

This application of the DEA bootstrap approach to measuring MFIs' efficiency reveals that the original method overestimated MFI efficiency. Thus, despite the reforms introduced during the nineties and early two-thousands, MFIs in the WAEMU can still improve their efficiency scores by an average of 36.39%. That inefficiency score is high compared to other studies that have been done on hospitals, where bootstrapped efficiency scores were 73% on average (Assaf and Matawie, 2010). Although hospitals and MFIs are not comparable, those results show that efforts must still be made for MFIs to be more socially and financially efficient.

Our study shows that there are large differences between the WAEMU member countries: efficiency scores range from 52% to 71%. Moreover, among the characteristics of MFIs, only the MFI type seems to strongly impact efficiency levels. Specifically, credit unions (among the other types of MFIs) have the highest levels of efficiency at approximately 66% on average.

Those differences remain questionable; therefore, we propose that future research deepens our analysis by looking at the causes of these differences. At present, our study seems to suggest that credit unions are the most efficient MFIs in both social and financial outcomes. Therefore, it would be wise for financial authorities in the WAEMU to encourage the creation and preservation of such MFIs in its member states.

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Appendix

Table IV. Estimates of CRS efficiency scores using the DEA bootstrap method of Simar and Wilson (2000).

DMU	Score(Original)	Bias	Mean	Median	SD	Lower Bound	Upper Bound
01	0,4706	0,0763	0,4383	0,4408	0,0211	0,3874	0,4666
02	0,4242	0,0444	0,4074	0,4136	0,0203	0,3480	0,4214
03	0,6106	0,1244	0,5473	0,5584	0,0466	0,4410	0,6043
04	0,5053	0,0485	0,4828	0,4890	0,0194	0,4295	0,5010
05	0,4419	0,0225	0,4323	0,4336	0,0054	0,4186	0,4387
06	0,6591	0,1082	0,5985	0,6132	0,0456	0,4934	0,6520
07	0,9396	0,1878	0,8040	0,8350	0,0962	0,5955	0,9240
08	0,4054	0,0716	0,3796	0,3858	0,0214	0,3284	0,4025
09	1,0000	0,6480	0,6728	0,6344	0,2106	0,3670	0,9842
10	0,2808	0,0395	0,2703	0,2723	0,0079	0,2513	0,2797
11	1,0000	0,1972	0,8510	0,8828	0,1063	0,5968	0,9820
12	0,8231	0,2107	0,6912	0,6945	0,0863	0,5153	0,8104
13	1,0000	0,7382	0,6572	0,6206	0,2225	0,2790	0,9829
14	1,0000	0,3734	0,7534	0,7010	0,1410	0,5538	0,9819
15	0,4475	0,2150	0,3781	0,3794	0,0575	0,2675	0,4508
16	0,2219	0,0515	0,2126	0,2199	0,0168	0,1727	0,2293
17	1,0000	0,3560	0,7731	0,8226	0,1549	0,4761	0,9791
18	0,3987	0,0202	0,3909	0,3915	0,0035	0,3822	0,3958
19	0,5291	0,0410	0,5089	0,5138	0,0176	0,4514	0,5248
20	0,5171	0,0264	0,5039	0,5053	0,0076	0,4861	0,5133
21	0,4443	0,1161	0,4025	0,4207	0,0396	0,3119	0,4410
22	0,6055	0,0794	0,5628	0,5725	0,0309	0,4856	0,5991
23	0,4699	0,0824	0,4361	0,4480	0,0279	0,3662	0,4656
24	0,6815	0,0759	0,6361	0,6501	0,0389	0,5252	0,6733
25	1,0000	0,8312	0,6462	0,6221	0,2347	0,2303	0,9826
26	0,6360	0,0527	0,6051	0,6116	0,0224	0,5344	0,6289
27	1,0000	0,3599	0,7808	0,8559	0,1710	0,4529	0,9794
28	1,0000	0,3081	0,7845	0,7690	0,1236	0,5667	0,9831
29	0,6943	0,0966	0,6360	0,6486	0,0412	0,5315	0,6855
30	0,8795	0,2883	0,7067	0,6997	0,1253	0,4678	0,8939
31	0,6491	0,1621	0,5680	0,5987	0,0691	0,4180	0,6416
32	1,0000	0,7333	0,6629	0,6302	0,2267	0,2688	0,9840
33	0,3632	0,0330	0,3519	0,3547	0,0092	0,3241	0,3610
34	0,5651	0,1183	0,5096	0,5250	0,0443	0,4044	0,5599
35	0,5954	0,0961	0,5451	0,5507	0,0315	0,4722	0,5886
36	0,4938	0,0369	0,4766	0,4798	0,0130	0,4355	0,4894
37	0,6972	0,1146	0,6346	0,6602	0,0666	0,4344	0,6895
38	1,0000	0,3867	0,7674	0,8323	0,1721	0,4377	0,9824
39	0,2164	0,0638	0,2047	0,2117	0,0149	0,1691	0,2175
40	1,0000	0,2719	0,8258	0,8893	0,1535	0,4450	0,9810