Research Journal of Finance and Accounting www.iiste.org
ISSN 2222-1697 (Paper) ISSN 2222-2847 (Online)
Vol.5, No.6, 2014

Microfinance Institutions' Efficiency in the MENA Region: a Bootstrap-DEA approach

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Abstract
The purpose of this study is to evaluate the performance of microfinance institutions in The MENA region over the period 2006-2009. Following Simar and Wilson (1998, 2000) we use a DEA-Bootstrapping methodology to drift appropriate measures of DEA efficiency scores. The estimated results show that average efficiency of the most countries in the region has decreased over the period under study. Results also reveal that efficiency significantly differs by legal status of the microfinance institutions.
Keywords: Microfinance, DEA, Bootstrap, MENA.
JEL: C14. G21.

1. Introduction

Microfinance generally refers to the provision of financial products and services to poor and low income households and their microenterprises. In the beginning, microfinance focused on providing only microcredit. The latter is the provision of small loans for income generating activities to the poor in most developing countries. However, lower income customers need a variety of financial services, not just microcredit. While lending remains a core activity, microfinance includes a broad range of financial services as micro-savings, micro-insurance, money transfers and other financial services. Microfinance institutions (MFIs) provide also non-financial services to their customers such as professional training, technical assistance, agricultural education or health care... in order to improve effectively the well-being of their clients (Flores and Serres, 2009). This sector involves a wide range of providers that vary in their legal structure, mission, methodologies and objectives. However, they share the common characteristic of providing financial services to poor individuals largely ignored by commercial banks and other financial institutions. MFIs have become an integral part of the financial sector in many developing countries. A significant proportion of the population in these countries is excluded from the formal financial sector, in particular: the poor, women, rural and micro-enterprises. Microfinance has proven to be an effective and powerful tool for poverty reduction and financial inclusion of thousands of poor and excluded people in these countries.

Microfinance institutions are special financial institutions, in addition to financial objective, they also have social or development objective, commonly termed the Double Bottom Line. Assessing the performance of a microfinance institution must account for two objectives. The first is related to the social impact of the organization and the second is rather the financial sustainability of the institution. Yaron (1994) introduced for the first time the dual concept of sustainability/outreach (or sustainability/impact) to evaluate the performance of MFIs. Financial sustainability is the ability of an institution to cover all its costs and expand its activity to a larger number of clients (Boyé and al., 2006). In general, it takes at least five years to achieve this goal for MFIs operating in urban areas and much more in rural areas. Sustainability has two levels: operational and financial. Operational sustainability reflects the ability of a MFI to cover its operating costs, while the financial sustainability is the ability of a MFI to cover all its costs and generate a margin to finance its growth. Financial sustainability reflects the ability of MFIs to continue their activities without resorting to subsidies or donations or concessional loans. Generally, MFIs are moving towards operational self-sufficiency in the short term, trying to assess financial sustainability in the long-term. In practice, most of MFIs fail to become financially viable. Most of them are still depending on subsidies (Morduch, 1999).

Social performance is a multidimensional concept; its assessment is both broader and more complex than financial performance. According to the Social Performance Task Force (SPTF) group, social performance is "*the effective implementation of an institution's social mission into practice. This mission may include serving larger numbers of poor and excluded people; delivering high-quality and appropriate financial services; creating benefits for clients; and improving the social responsibility of a MFI*" (CGAP[2], 2007).

In First studies (Cornée, 2006; Gutiérrez-Nieto and al., 2007, 2009; Cull and al., 2007, Hermes and al., 2009) social performance was generally measured by the outreach of social program which includes: (i) the breadth of

[2] Consultative Group to Assist the Poorest.

outreach measured by the ability of an institution to reach as many customers as possible in a given period and (ii) the depth of outreach measured by the ability to reach the poorest (those whose social position is initially depressed). Traditional indicators of outreach includes the number of borrowers, total loan portfolio (these are measures of the breadth of outreach), average loan balance per borrower and ratio of average loan balance to GNP per Capita (these are measures of the depth of outreach), etc. According to Lapenu and al., (2009), these proxies only give a vague idea of outreach ignoring many of the other dimensions of social performance such as the adaptation of financial services and their impact on social welfare. Moreover, they only account for credit operations and ignore by the fact the other aspects of microfinance. In recent years social performance assessment has evolved significantly, with the development of social audits, social ratings and reporting standards.

The present work aims to measure the performance of MFIs in MENA region by using the non parametric Data Envelopment Analysis (DEA) method following the literature. However, DEA models have many drawbacks which are dealt with in this paper. First we use Simar and Wilson (2002) bootstrap-based approach to test the nature of return to scale of the different MFIs. Secondly, all the non parametric estimators of frontiers are particularly sensitive to atypical observations and outliers. To detect outliers we use a combination of three methods, the peer-count index (Charnes and al., 1985), the super-efficiency approach (Anderson and Petersen, 1993) and Wilson approach (Wilson, 1993). After clearing the data from outliers, following Simar and Wilson (1998, 2000) we use a DEA-Bootstrapping methodology to drift appropriate measures of DEA efficiency scores and to construct confidence intervals.

The rest of the paper is organized as follows. Second section reviews theoretical and empirical literature. The third section presents the main features of microfinance in the MENA region. Section four develops the methodology adopted in this paper. In section five we present data, we select inputs and outputs and we specify the model. Section six is concerned by the model orientation and the specification of the returns to scale. Section seven deals with the detection of outliers. In section eight we calculate the bias-corrected efficiency scores. Section nine studies the evolution of the scores calculated in section eight and the last section concludes.

2. Literature review

In recent years, there are a growing number of studies applying efficiency and productivity techniques to evaluate the performance of microfinance institutions. Most of the studies have used the non-parametric DEA to assess the efficiency of MFIs all around the world. Nghiem and al. (2006) are the only to use both parametric and non-parametric approach. The implementation of the two approaches leads to similar estimates/scores of the MFIs' efficiency. Mamiza, Michael and Shams, (2010) analyzed the cost efficiency of 39 microfinance institutions in Africa, Asia and Latin America by applying the DEA method. The results showed that non-governmental organizations (NGOs) are the most efficient given the production approach, while under the intermediation approach, banks providing microfinance services are most efficient. As financial intermediaries, banks have the competitive advantage of access to local capital as well as global financial markets which is not the case for NGOs.

Gutiérrez-Nieto et al. (2007) have adopted a DEA and multivariate analysis methodology to evaluate the performance of 30 MFIs in 21 Latin American countries using different combinations of inputs and outputs. This approach consists on determining in a first stage, the efficiency scores under different specifications. In a second stage the principal component analysis is used to explain differences in efficiency scores. None of these institutions has been efficient in all the specifications. According to Gutiérrez-Nieto and al. (2007) the level of efficiency depends on the specification chosen, which shows the importance and delicacy of the selection step of inputs and outputs. The results set evidence of the existence of a country effect and a non-governmental organization status effect (NGO/ no-NGO). They conclude that NGOs are more efficient because of their ability to serve many customers while minimizing costs. This merely reaffirms the pursuit of the double goals of sustainability and social impact. The evaluation of efficiency of 35 microfinance institutions in the Mediterranean countries during the period 2004-2009 by Ben Soltane (2008) revealed the existence of relatively 8 efficient MFIs. Ben Soltane found that the size of MFI plays a negative role in its efficiency. It means that medium size institutions are more efficient than the others. The author concluded that the key of success of MFIs is their ability to establish, due to their small size, a relationship of trust with their customers which could have resulted in lower transaction costs. Without loss of generality, the most frequently cited studies are referred in table 1 in the appendix.

Our paper contributes to the existence empirical literature and goes beyond in many ways. First, contrary to the previous studies which don't test the nature of return to scale, our study investigates empirically to determine if returns to scale are constant or variable. Second, in order to detect outliers we use three procedures (peer-count index, Wilson approach and the super-efficiency concept). Finally, we use a robust DEA-bootstrapping methodology to estimate unbiased efficiency scores and to construct confidence intervals.

3. Microfinance in MENA region

This study focuses on the microfinance sector in the MENA region, which is currently booming. Till recent years, the majority of studies on microfinance have focused on the regions of Latin America, North Africa and Asia, while studies on microfinance in the MENA region are scares. At our knowledge, there are only three published studies that have investigated the case of microfinance in the Arab region (Ben Soltane, 2008; Omri and Chkoundali, 2011 and Adair And Berguiga, 2010). Ben Soltane (2008) applies the non-parametric DEA method to assess the efficiency of 35 Microfinance institutions in the Mediterranean zone during the period of 2004–2005 while Omri and Chkoundali (2011) and Adair and Berguiga (2010) examine the nature of the relation between financial and social performance of the MFI in the same region. In addition, the Regional Microcredit Summit held in April 2010 in Nairobi (Kenya) was devoted to Africa and the Middle East, which proves the growing interest to microfinance in the region. The summit was intended to assess progress towards the goals of the Campaign for year 2015 and also to share best practices and accelerate innovative measures.

The microfinance sector in MENA is a relatively young industry compared to other regions where microfinance was developed over thirty years (MMW[3], 2003). Although the microfinance sector in MENA is dominated by NGOs and solidarity group lending methodology, it is beginning to experience diversity in institutional forms and services to customers. According to a recent benchmarking report published in April 2009[4], the microfinance sector in the region has intensified its activities by providing access to financial services to more customers and by expanding the range of products offered especially individual products. MFIs in MENA have focused more on education and on understanding the needs of their customers. To this end, new loan products have been designed to meet these needs. The services offered by Arab MFIs remain limited to loans, mainly loans to micro-enterprises (MMW, 2009). Although Arab MFIs have offered more group loans in the past, especially to female borrowers with small self-employed activities, they are now shifting their focus to more micro-entrepreneurs at the higher end of the market (MMW, 2010).

Savings products continue to be offered on a limited scale in the region due to restrictions in legislation. Within this region, the two major market players are Morocco and Egypt. They currently include, alone, 85% of the number of total borrowers and 73% of the total loan portfolio in the region (MMW, 2010). Morocco is in the first place and has evolved much faster with a large step ahead of its Arab peers. The implementation of microfinance programs in Morocco was immediately transformed into a "success story". However, this country has faced over the period 2008-2010 a crisis caused by a sharp deterioration in the quality of its loan portfolio. In third place we find Jordan pursued by Tunisia. Other countries are far behind.

Despite a slowdown in the global economy and a global financial crisis, the microfinance sector in the MENA region has continued its development. In terms of infrastructure, there was the opening of new branches and staff hiring. At the operational level, significant growth in the loan portfolio was recorded and the products offered are becoming more diversified. According to a recent benchmarking report published by the MIX in May 2010, the microfinance sector in the Arab region recorded the second highest median, after Asia, in terms of outreach. On average, an Arab MFI reached 11785 borrowers in 2008, surpassing the most mature market of Latin America and the Caribbean (LAC), where a MFI reaches an average of 9768 borrowers. In terms of Gross Loan Product (GLP) growth, the Arab region also ranked second globally – this time to LAC– with respect to median GLP, which reached approximately 5.1 million USD per MFI. The region registered an increase in both GLP and number of borrowers by 69% and 43%, respectively, over the period 2006-2008, although a worldwide slowdown in growth in 2007 and 2008. However, the Arab microfinance sector is still facing many challenges, especially at the regulation level. In addition, to strengthen their activities, MFIs also need good governance, appropriate microfinance investment structure and internal credit policies and controls (MMW, 2009). It is therefore of utmost interest to investigate the efficiency of microfinance institutions in this region.

4. Empirical Methodology

The performance assessment in this paper is based primarily on the use of efficiency frontiers, which have emerged as a better alternative to the traditional analysis by the ratios (Lafourcade and al. (2005); Yaron (1994)). To assess the performance of the microfinance institutions we use the non-parametric DEA method following the literature (Gutiérrez-Nieto and al. (2007); Ben Soltan B. (2008); Cornée S. (2007); Gutiérrez-Nieto and al. (2009) and others). However, Simar ad Wilson (1998, 2000) noted that the traditional DEA methodology estimation is biased by construction and is affected by uncertainty due to sampling variation and suffers of the curse of dimensionality. Given that, we apply a DEA-Bootstrapping proposed by Simar and Wilson (1998, 2000) to derive unbiased DEA estimators.

[3] The Mix Microfinance World find microfinance country, regional, and/or global analysis based on the MIX Market database, the most complete source of financial and social performance information.

[4] This report was conducted by the MIX (Microfinance Information Exchange) in collaboration with the network Sanabel, which is the network of microfinance in Arab countries.

4.1 *DEA-Bootstrapping approach*

The DEA method is an analytical tool to assess the relative efficiency of a number of producers operating in the same industry. Assuming that the activity of a MFI *i, i=1,...,n,* is described by a set of inputs $x_k \in \Re_+^p$ which are converted into a set of output $y_k \in \Re_+^q$ through a production technology. The production technology is available for each MFI in the sector (common frontier). The set of technically feasible combinations of inputs and outputs such that the input *x* can produce the output *y* is defined as:

$$\Psi=\{(x,y)\in \Re_+^p \times \Re_+^q \,|\, x \text{ can produce } y\} \qquad (1)$$

Since the real technology is unknown, the DEA variable return to scale (VRS) estimator of the attainable Ψ set is obtained as follows:

$$\hat{\theta}_{VRS}(x,y)=\inf\{\theta \,|\, (\theta x,y)\in \hat{\Psi}_{VRS}\} \qquad (2)$$

$\hat{\theta}_{VRS}(x,y)$ can be computed by solving the following linear program:

$$\hat{\theta}_{VRS}(x,y)=\min\{\theta>0 \,|\, y\le \sum_{i=1}^{n}\gamma_i y_i;\theta x\ge \sum_{i=1}^{n}\gamma_i x_i\, for(\gamma_1,....\gamma_n);\sum_{i=1}^{n}\gamma_i=1 \text{ and } \gamma_i\ge 0\} \qquad (3)$$

Alternatively, if we assume constant return to scale (CRS):

$$\hat{\theta}_{CRS}(x,y)=\min\{\theta>0 \,|\, y\le \sum_{i=1}^{n}\gamma_i y_i;\theta x\ge \sum_{i=1}^{n}\gamma_i x_i;\gamma_i\ge 0\} \qquad (4)$$

In $\hat{\theta}_{VRS}$ we have the convexity constraint $\sum_{i=1}^{n}\gamma_i = 1$ which is dropped in $\hat{\theta}_{CRS}$.

However, as stated by Simar and Wilson (2008), the non-parametric efficiency scores are biased by construction and the bias depends mainly on the sample size (the number of units under analysis) and the dimension of the model (the number of inputs and outputs).

The bias is equal to:

$$\text{BIAS}\left(\hat{\theta}(x,y)\right)\equiv E\left(\hat{\theta}(x,y)\right)-\theta(x,y) \qquad (5)$$

Simar and Wilson (2000) propose an improved procedure which corrects for bias. The procedure is presented below in terms of the difference $\hat{\theta}_i(x,y)-\theta_i(x,y)$. At this essence, Simar and Wilson (2000) have developed an algorithm based on bootstrapping techniques. We should note that the essence of the bootstrap idea (Efron, 1979, 1982; Efron and Tibshirani, 1993) is to approximate the sampling distributions of interest by simulating or mimicking the data generating process (DGP). The purpose of the algorithm developed by Simar and Wilson (2000) is to mimic the distribution of DEA scores $\hat{\theta}_i(x,y)$, in order to approximate the real one $\theta_i(x,y)$. As the real one is unknown, $\{\hat{\theta}_i(x,y)-\theta_i(x,y)\}$ is unknown as well. In this case appropriate bootstrap approximation provides opportunity to proxy $\{\hat{\theta}_i(x,y)-\theta_i(x,y)\}$ to the bootstrap counterpart $\{\hat{\theta}_i^*(x,y)-\hat{\theta}_i(x,y)\}$ where $\hat{\theta}_i^*(x,y)$ are bootstrap estimates, completely known one supposed $\hat{\theta}_i(x,y)$ as true[5]. Having mimicked the distribution, statistical properties of each unit can be derived as follows: the bias and the standard deviation are estimate as:

$$\widehat{BIAS}(\hat{\theta}_i)=E\left(\hat{\theta}_i\right)-\theta_i^*=\text{B}^{-1}\sum_{b=1}^{B}\theta_{i,b}^*-\theta_i^*\;\forall i=1,....,n \qquad (6)$$

Where $\hat{\theta}_{i,b}^*$, is the bootstrapped efficiency scores and B is the number of replications.

$$\widehat{std(\hat{\theta}_i)}=\left[\frac{1}{\text{B-1}}\sum_{b=1}^{B}(\hat{\theta}_{i,b}^*-\bar{\theta}_{i,b}^*)^2\right]^{1/2} \qquad (7)$$

With $\bar{\theta}_{i,b}^*$ the mean of the bootstrapped efficiency scores.

The bias-corrected DEA efficiency scores ($\hat{\theta}_i^c$)are obtained by subtracting the bias from the original scores as follows:

$$\hat{\theta}_i^c=\theta_i-\widehat{BIAS}\left(\hat{\theta}_i\right)=2\theta_i-B^{-1}\sum_{b=1}^{B}\theta_{i,b}^* \quad \forall i=1,....,n \qquad (8)$$

The DEA efficiencies are corrected in (8) unless:

$$\frac{|\widehat{BIAS(\hat{\theta}_i)}|}{\widehat{std(\hat{\theta}_i)}}>\frac{1}{\sqrt{3}} \quad \forall\, i=1,\dots,n \qquad (9)$$

Alternatively, Efron and Tibshirani (1993) propose a less conservative rule, suggesting that the bias correction can be avoided unless

$$\frac{|\widehat{BIAS(\hat{\theta}_i)}|}{\widehat{std(\hat{\theta}_i)}}>\frac{1}{4} \quad \forall\, i=1,\dots,n \qquad (10)$$

As the bootstrap distribution $(\hat{\theta}_{i,b}^*-\hat{\theta}_i)$ is completely known, the relative quartiles α_α^* and β_α^* for a given level

[5] Theoretical properties of the bootstrap with DEA estimators are provided in Kneip et al. (2003).

of probability could be then easily obtained.

5. Data and input-output selection

The data source is the "Microfinance Information Exchange" (MIX)[6] the first source for objective, qualified and relevant microfinance performance data and analysis. MIX provides actually access to financial and social performance information covering approximately 2000 MFI implemented around the world. Our sample is composed of an unbalanced data of 61 MFIs from MENA region (Egypt, Iraq, Jordan, Lebanon, Morocco, Palestine, Sudan, Syria, Tunisia and Yemen) over the period 2006-2009, all of which have a disclosure level of 3 or higher[7]. Following the MIX classification of MFIs, our set contains 46 NGO, 10 non-bank financial institutions (NBFI), 1 bank and 4 others.

5.1 Model specification

One of the major problems of the DEA approach is the difficulty to specify the model. The theory underlying DEA is not restrictive on how the variables should be selected, or in the number of variables that must be included in the model. We should note, however, that if the number of variables is relatively high, the model will be less discriminating in the sense that more efficient MFI will be declared and vice versa. DEA researchers have suggested a rule of thumb for the relation between the number of observations (units or firms) and the number of inputs and outputs (Bogetoft and Otto, 2011). Traditional rules suggest that the number of firms, designed by n, must exceed 3 times the number of inputs and outputs ($n > 3(p + q)$) and must exceed the product of the number of inputs and the number of outputs ($n > pq$). The two rules are verified in our study.

Several criteria can be used for the identification of inputs and outputs. In this study, we will select variables according to the literature survey and the availability of the data. Inputs and outputs should take into account both objectives of MFI: social and financial. The inputs selected in this study are standard in the literature (Guitiérrez-Nieto and al., 2009): total assets (TA), operating expenses (OEX) and number of employees (NE). Outputs are of two types. One Indicator of financial performance: financial revenue (FR) and a social performance indicator developed by (Guitiérrez-Nieto and al., 2009) which is an indicator of benefit to the poorest (POV). Table 2 presents the inputs and outputs selected in the study and their definitions. Table 3 in appendix summarizes the descriptive statistics.

Table 2: Inputs and outputs included in the DEA model

Variables	Definition
Inputs	
1. Total Assets (TA)	Total of all net asset accounts
2. Operating expenses (OEX)	The total value of all operating expenses, including personnel and administrative expenses, incurred in providing financial services.
3. Number of employees (NE)	The number of individuals who are actively employed by the IMF.
Outputs	
1- Indicator of benefit to the poorest (POV)	$POV = pov_i \times number\ of\ active\ borrowers$ (Guitiérrez – Nieto & $al.$, 2009) $pov_i = 1 - \frac{k_i - Min(k)}{Range(k)}$ *with k=Average loan balance per borrower/Gross National Income per capita.* And *i* is an indicator associated with a particular MFI , *i* = *1,…,n.*
2. Financial revenu (FR)	The total value of all revenue earned from the provision of financial services.

Note: Total assets, operating expenses and financial revenue are expressed in $US.

Gutiérrez-Nieto and al. (2009) have tried to construct an indicator that takes into account both aspects of outreach: depth and breadth. The breadth of outreach is measured by the average loan per borrower/GNI (k) per capita. To standardize this value to 0, 1, the authors remove the minimum value of k in the set and divided it by the range of k. Value near 0 means that the MFI is reaching the very poor. As the authors prefer a value near 1 to be associated with the objective or reaching the poorest, to simplify the interpretation of the index, they deduct

[6] Incorporated in 2002, MIX is a non-profit organization headquartered in Washington, DC with regional offices in Azerbaijan, India, Morocco, and Peru. MIX provides objective, qualified and relevant performance information on microfinance institutions (MFIs), funders, networks and service providers dedicated to serving the financial sector needs for low-income clients.

[7] Based on the level and quality of disclosure of the MFI, MIX Market uses a rating system, where the scores range from 1 to level 5.

the previous value ($\frac{k_i - Min(k)}{Range(k)}$) from one. To measure the depth of outreach they use the number of active borrowers and by multiplying the two measures they construct an indicator of outreach (*POV*). The value of this index reflects the commitment of an institution in fighting the poverty, a higher value of *POV* is associated with a better outreach of the MFI.

6. *Returns to scale and model orientation*

Before analyzing DEA efficiency values, one might question whether or not the frontier exhibits constant or variable returns to scale. Coelli and al. (2005) indicated that the constant return to scale (CRS) assumption is appropriate when all firms operate at an optimal scale. They noted, however that many reasons such us imperfect competition, government regulations, financial constraints and so forth, may cause a firm to operate at sub-optimal level. The use of the CRS in such case will result in measures of technical efficiency that is confounded by scale efficiency (Coelli and al., 2005). In order to avoid the scale efficiency effects, variable return to scale (VRS) are therefore applied to calculate technical efficiency. Some authors adopt Charnes, Cooper and Rodes (CCR) model of constant return to scale (Gutiérrez-Niéto and al., 2007, 2009), while others assume both constant and variable return to scale (Haq and al., 2010, Ben Soltane, 2006). However, none of these authors stands the test of scrutiny. Simar and Wilson (2002) have noted that assuming a CRS technology without investing the possibility that returns to scale are not constant incurs the risk of inconsistently estimating technical efficiency. Daraio and Simar (2007) noted that the VRS estimators are consistent whatever being the hypothesis on return to scale, but the CRS are only consistent if the CRS hypothesis is true. For this purpose, we apply the Simar and Wilson (2002) bootstrap-based approach to test the nature of return to scale of the different Arab MFIs. This approach consists to test if the technology set Ψ exhibits constant return to scale by using bootstrap method to test hypothesis. Formally, Simar and Wilson (2002) establish the following tests:

Test1 $\quad H_{10}$: Ψ is globally CRS
$\quad H_{1A}$: Ψ is VRS

If H_{10} is rejected, then we have to perform another test with a less restrictive null hypothesis.

Test2 $\quad H_{20}$: Ψ is globally NIRS
$\quad H_{2A}$: Ψ is VRS

The statistic is the mean of the ratio of the efficiency scores:

$$\hat{S}_{1n}^{crs} = \frac{1}{n}\sum_{i=1}^{n}\frac{\hat{\theta}_n^{crs}(x_i, y_i)}{\hat{\theta}_n^{vrs}(x_i, y_i)} \qquad (11)$$

As $\hat{S}_{1n}^{crs} \leq 1$ by construction, we will reject H_{10} if the test statistic $\hat{S}_{1n}^{crs}$ is too small.

The *p*-value of the null-hypothesis is then obtained by computing:

$$\text{p-value}=P\left(\hat{S}_{1n}^{crs} < \alpha_c \middle| H_{10}\right) \qquad (12)$$

Given the fact that S_{1n}^{crs} is unknown under H_{10}, we cannot calculate α_c directly. One way to address this lack of distributional knowledge is to use a bootstrap method. The orientation of the model should be also selected. According to Coelli and al. (2005), the choice of an appropriate orientation has, in many instances, only a minor influence in the scores obtained. If the constant return to scale prevails, the results of technical efficiency measures would be very similar irrespective of the output-oriented or input oriented method (Simar and Daraio, 2007). However the results differ under increasing or decreasing return to scale (Fare and Lovell, 1978).

We apply the bootstrap algorithm described above to test the nature of return to scale following Simar and Wilson (2002). We calculate the CRS and the VRS efficiency sores and the test statistic S_{1n}^{crs}, *p-values* are presented in table 4. We obtain for this test (*with B=2000*) a *p-value* >0.05 for the four years under study; hence we cannot reject the null hypothesis of CRS. Given the CRS assumption, in what follows we adopt an input orientation of the model.

Table 4: Tests of returns to scale: *p-values*

Year	**2006**	**2007**	**2008**	**2009**
p-value	0.227	0.216	0.285	0.226

Source: Author's elaboration

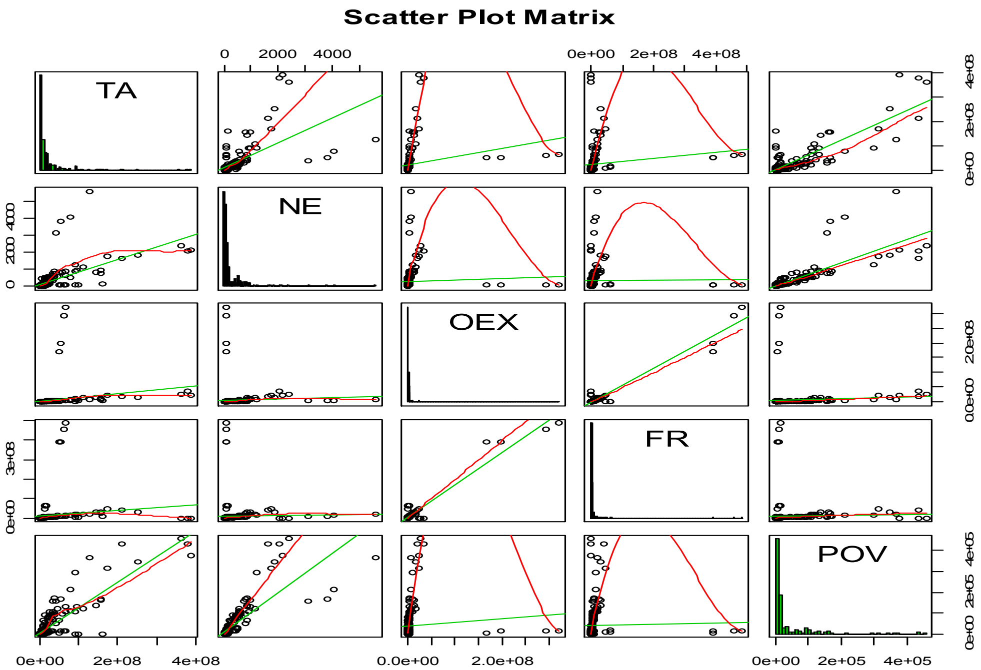
7. Outlier detection

One of the main drawbacks of the DEA estimator is its sensitivity to extreme values and outliers. Simar (2003) stressed out the need for determining and eliminating outliers when using deterministic models. A number of methods have been proposed in the literature to detect outliers[8]. According to Simar (2003), no optimal procedure exists in the context of frontier model and no method is perfect. We have than to use a combination of methods to detect potential outliers or influential observations. For the purpose of this study, we will use three

[8] For a review of the methods proposed to detect outlier observations see Simar et Wilson(2008).

outlier detection procedures which are the peer-count index (Charnes and al., 1985), the super-efficiency approach (Anderson and Petersen, 1993) and Wilson method (Wilson, 1993).
As a first detection procedure, we use the super-efficiency procedure introduced by Anderson and Peterson (1993). Super-efficiency measures are constructed by avoiding that the evaluated firm can help span the technology that is by ensuring that a unit cannot affect its own benchmark. This score is obtained by removing the unit in question from the full data set used when calculating the efficiency scores, and then calculating the efficiency score of the unit against this new frontier. The efficiency score will normally be greater than (or equal to) one, hence the term of "super-efficiency". The larger the super-efficiency of a DMU, the farther it is from the rest of the units in the assessment set. Firms are considered as potential outliers if their input (output) super-efficiency is large (say 3 or 4), it means that it is significantly pushing out of the frontier (Bogetoft and Otto, 2011).
The second outlier detection procedure to be used is the peer count index suggested by Charnes and al. (1985). This method consists on the simple computation of the number of times an efficient unit is peer of an inefficient unit. In other word, it gives the number of occurrences as referencing unit. The peer count shows number of appearances, but without discriminating between differing peer influence on the reference point of the inefficient units, while the Super efficiency score tells us about the influence on the shape of the production frontier. Observations with higher or lower peer count can be considered as candidates to be outliers.
Rather than checking efficiency scores, Wilson (1993) extends Andrews and Pregibon's (1978) statistics to suggest some outlier detection methods by looking directly at inputs and outputs. Wilson (1993) proposed another method employing an influence function based on the geometric volume spanned by the sample observations and the sensitivity of this volume with respect to deletions of singletons, pairs, triplets and so forth, from the sample. For more details see Wilson (1993).
By combining many procedures we are able to detect for each year a range of potentially interesting atypical observations. We should note, however, that once we have detected potential outliers we have to decide what to do with them, these are two separate issues (Simar and Wilson, 2008). A simple way to see if there might be a problem with outliers is to make a graphical display of the data (Simar and Wilson, 2008; Bogetoft and Otto, 2011). In this case, a useful tool can be the scatter plot matrix.

Fig1: Scatterplot matrix of the data set: 3 inputs and 2 outputs, Histogram of the variables on the diagonal.



In this graph, there are signs of outliers. Some firms seem to have larger inputs and outputs than others. We can see that there are dots above all the other grouped dots. Hence we have checked to make sure of the existence of potential outliers. we now apply the three methods presented above to detect them. Results are presented in table 4 in the appendix.
There seems to be a consensus between the three methods used. The procedures identified three potential outliers, 1 Lebanon (Al Majmoua), 1 Jordan (DEF) and 1Morocco (Zakoura). The outlying observations are the same from peer-count index and super-efficiency approach but differ from the Wilson (1993) method in which we

equalized i to 12. Having identified potential outliers, we have now to decide whether or not to remove them from the data set. We remove the observations that are detected as potential outliers from at least two methods. Given that, we eliminate on average 6 outlying MFI for each year as determined by the three procedures.

8. Bootstrapping efficiency scores

After clearing the data set from outliers, we compute the input-oriented CRS bootstrap DEA estimates. Results are obtained from 2000 replications. The homogeneous bootstrap method described by Simar and Wilson (1998, 2000) is used to estimate confidence intervals for Shephard (1970) input distance functions[9]. The input efficiency measure is the reciprocal of the shepahard (1970) intput distance function. To obtain the efficiency scores we have only to inverse the distance function:

$$\delta(x,y) \equiv \frac{1}{\theta(x,y)} \qquad (13)$$

The results indicate substantial bias, since the bias estimates are large relative to the standard error estimates, than; the bias-corrected efficiency estimates are preferred to the original estimates. We have also to note that none of the resulting efficiency bias-corrected estimates equals one. Although the fact that the sample size is rather small in this high-dimensional problem, the confidence intervals are of moderate length except for certain MFIs. The average width for the bootstrap estimates of 95%- confidence intervals amounts to 0.43. A MFI with an efficiency score higher than one is relatively inefficient with respect to its benchmarks. Average results by country are presented in table 5.

Table 5: Average bootstrap results (Shephard distance function)

Country	Original eff.	Bias-corr eff.	Bias	Variance	Lower bound	Upper bound
Egypt	1.394	1.592	-0.1981	0.0109	1.4143	1.786
Iraq	2.1669	2.4362	-0.2693	0.0238	2.1988	2.7212
Jordan	1.5528	1.7425	-0.1897	0.0156	1.5729	1.9545
Lebanon	2.2842	2.5326	-0.2484	0.0236	2.3097	2.8209
Morocco	1.3067	1.4771	-0.1704	0.0097	1.3252	1.6434
Palestine	2.4298	2.7147	-0.2849	0.0387	2.4588	3.0302
Sudan	1.9248	2.1886	-0.2638	0.027	1.9526	2.4574
Syria	1.7679	2.0545	-0.2866	0.0288	1.794	2.3699
Tunisia	1.0307	1.1485	-0.1179	0.0027	1.0469	1.2521
Yemen	1.1911	1.3713	-0.1803	0.0085	1.2082	1.5454

Source: Author's elaboration

The average efficiency is equal to 1.70 which indicates that an average MFI could decrease its inputs by 41.34% while keeping its outputs constant. While original estimates lie for every country outside, but close to the lower bound of the confidence interval, bias corrected estimates lie inside this interval. This is due to the upward bias

Table 6: Summary statistics for efficiency estimates (Farrell input efficiency estimates)

	Year	Number of MFI	Mean	Sd.	Median	Min	Max
	2006						
Efficiency estimates		40	0.83	0.19	0.89	0.17	1
Bias-corrected efficiency		40	0.76	0.17	0.82	0.16	0.92
Bias		40	0.08	0.04	0.07	0.01	0.17
	2007						
Efficiency estimates		47	0.72	0.24	0.74	0.18	1
Bias-corrected efficiency		47	0.62	0.2	0.63	0.16	0.9
Bias		47	0.1	0.05	0.09	0.02	0.23
	2008						
Efficiency estimates		52	0.74	0.24	0.76	0.08	1
Bias-corrected efficiency		52	0.64	0.2	0.68	0.07	0.9
Bias		52	0.1	0.06	0.08	0.01	0.24
	2009						
Efficiency estimates		54	0.68	0.25	0.68	0.16	1
Bias-corrected efficiency		54	0.60	0.22	0.6	0.15	0.9
Bias		54	0.08	0.05	0.07	0.01	0.22

Source: Author's elaboration

[9] The efficiency scores are computed by the use of the statistical program *R* and its package 'FEAR' developed by Wilson (2005).

of the original estimator and to the bootstrap correction in the confidence interval. We report the summary statistics of the Farrell original and the bias-corrected efficiency estimates in table 6. The mean efficiency for the original scores for the year 2006 is 0.83, this implies that the mean potential for input savings among MFIs is equal to 17%. For individual years, we can observe fluctuations in average score for both original and bias-corrected estimates. The results show that the mean efficiency and the mean bias-corrected efficiency decreased respectively from 0.83 and 0.76 in 2006 to 0.68 and 0.60 in 2009. The rate decrease in the efficiency of MFI was more important in 2007 about 13% for the original estimates and 18% for the bias-corrected estimates, this is probably due to the global economic crisis. The average efficiency has slightly increased in 2008 and dropped again in 2009.

9. Efficiency evolution

Fig.2 displays the geometric mean of the bias-corrected efficiency of the MFIs grouped by country for the period 2006-2009. It can be noticed that the efficiency of the most countries of the region has declined in 2007. Even MFI from Morocco, the historical market leader, which has strong growth in the preceding year, has shown a decrease in the average efficiency. Morocco is one of the countries which appears to be very affected, but for reasons that are not directly related to the global crisis. This country, in particular, has faced a crisis due to a deep deterioration in loan portfolio quality. However, according to a recent study of the CGAP, Morocco MFIs had embarked in a path of recovery with timely support of the government. This decrease in the efficiency doesn't seem to slow down especially for Morocco, Iraq and Palestine. Despite the fact of global decrease in the regional performance, growth continued but at slower rates in 2008 and 2009 in Egypt and Tunisia.

Fig. 2 Evolution of the bias-corrected efficiency of the MFIs grouped by country

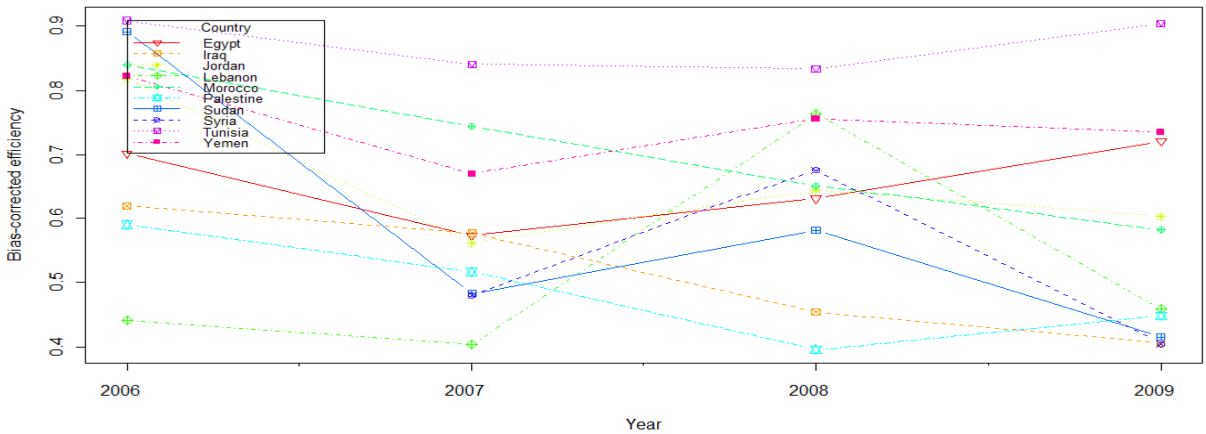
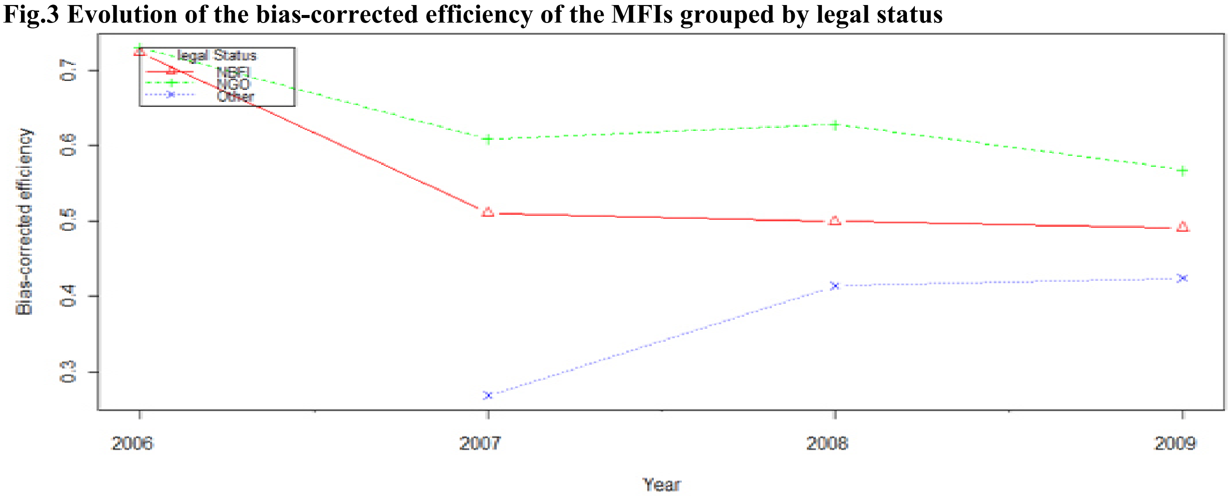


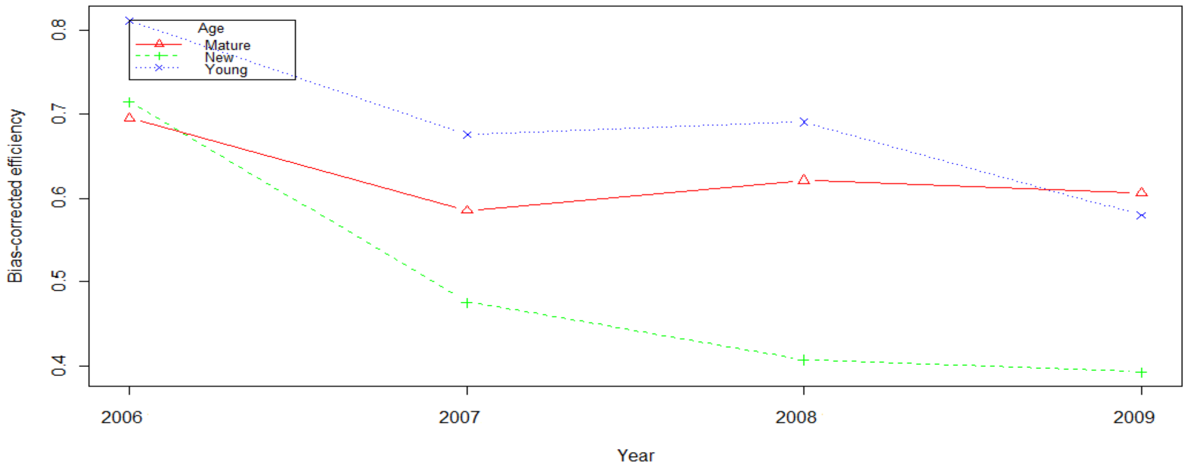
Fig.3 Evolution of the bias-corrected efficiency of the MFIs grouped by legal status



We have also to note that young and emerging markets in the region, with some exceptions, have the lowest efficiency in the region such as Syria, Sudan, Lebanon and Palestine. However Yemen, which is also a nascent market, seems to perform well comparing to other countries. The figure also shows striking disparities in performance of the microfinance market among the different countries included in the sample as well as fluctuations in performance from one year to another.

Fig.3 shows the evolution of the bias-corrected efficiency (geometric mean) over time of MFIs grouped by legal status. At the industry level over time the average efficiency of NGO seems to be significantly greater than those of the NBFI, which confirms the findings of other studies (Guitiérrez-Nieto and al., 2009; Ben Soltane, 2008; Adair and Berguiga; 2010). This is due to their higher level of outreach. Actually, the main objective of NGO is to seek social performance, which can be evaluated in terms of quality of service provided by the organizations.

Fig.4 Evolution of the bias-corrected efficiency of the MFIs grouped by age



The MIX classifies MFI into three categories (new, young and mature) based on the maturity of their microfinance operations[10]. New MFIs have 1 to 4 years, Young MFIs have from 5 to 8 years and finally mature institutions have more than 8 years. As human activity is subject to learning process, mature MFIs are expected to become more efficient in achieving its objectives. However, it doesn't seem to be the case for MFIs (Fig.4), since young MFIs are more efficient, over time, than mature MFI. Guitiérrez-Nieto and al., (2009) studied the relationship between age and MFIs' efficiency and found a very low correlation. It should mean that mature MFIs are becoming large and not necessarily more efficient.

10.Conclusion

In this study we have assessed the efficiency of microfinance institutions in the MENA region and we have taken it one step further by using a robust non-parametric approach. First we have applied the Simar and Wilson (2002) methodology to test the nature of return to scale of the different MFIs. Secondly, we have used a combination of three methods, the peer count (Charnes and al., 1985), super-efficiency approach (Anderson and Petersen, 1993) and Wilson approach (Wilson, 1993) to detect outliers. After clearing the data from outliers, following Simar and Wilson (1998, 2000) we have used a DEA-Bootstrapping methodology to drift appropriate measures of DEA efficiency scores and to construct confidence intervals. The estimated results show that average efficiency of the most countries of the region has decreased over the period under study. Results also reveal that efficiency significantly differs by legal status. At the industry level over time, the average efficiency scores of NGO are greater than those of the NBFI. Although we have exploited advanced bootstrapping tools when applied to DEA, it would be better if we have implemented a second stage DEA approach where the observed efficiency patterns are explained using a set of environmental factors.

References

Adair, P.H. And Berguigua, I. (2010) Les facteurs déterminants de la performance sociale et de la performance financière des institutions de microfinance dans la région MENA : une analyse en coupe instantanée. Région et développement, 32, pp. 91-119.
Andersen, P. and Petersen, N. C. (1993) A procedure for ranking efficient units in data envelopment analysis. Management Science, 39 (10), pp.1261–1264.
Andrews, D. F. and Pregibon, D. (1978) Finding the outliers that matter. Journal of the Royal Statistical Society, 40, pp. 85–93.
Ben Soltane, B. (2008) Efficiency of Microfinance Institutions in the Mediterranean: An Application of DEA. Transition studies review, Mediterranean and Middle East Papers, 15(2), pp. 343-354.
Bogetoft, P. and Otto, L. (2011) Benchmarking with DEA, SFA and R. (Springer).
Boyé, S., Hajdenberg, J. and Poursat, C. (2006) Le guide de la microfinance: microcrédit et épargne pour le

[10] This is calculated as the difference between the year they started their microfinance operations and the year of data submitted by the institutions.

développement, (Organisation edition).

Charnes, A., Cooper, W., Golany, B., Seiford, L. and Stutz, J. (1985) Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. Journal of Econometrics, 30, pp. 91-107.
CGAP, (2007) Measuring the social performance of microfinance institutions. Focus note 41.
Coelli, T. J., Prasada Rao, D.S., O'Donnell, Ch.J. and Battese, G.E. (2005), An introduction to efficiency and productivity analysis. 2nd edition. (Springer).
Cornée, S. (2007) Au-delà de la nécessité de considérer les performances sociales dans la microfinance: une proposition d'évaluation conjointe des performances sociales et financières en microfinance. Document de travail N 3, Cerise, pp. 1-17.
Cull, R., Demirgüç-Kunt, A. and Morduch, J. (2007) Financial performance and outreach: A global analysis of lending microbanks. The Economic Journal, 117, pp. 107–133.
Daraio, C. and Simar, L. (2007) Advanced robust and nonparametric methods in efficiency analysis.Methodology and applications (Springer, New York).
Efron, B. (1979) Bootstrap methods: another look at the jackknife. Annals of Statistics 7, pp. 1–16.
Efron, B. (1982) The Jackknife, the Bootstrap and Other Resampling Plans. CBMS-NSF Regional Conference Series in Applied Mathematics, N°38, Philadelphia: Society for Industrial and Applied Mathematics.
Efron, B. and R.J. Tibshirani (1993), An Introduction to the Bootstrap, London: Chapman and Hall.
Fare, R. and Lovell, C. (1978) Measuring the technical efficiency of production. Journal of Economic Theory, Vol.19, pp. 150–162.
Flores, I. L. and Serres, Ph. (2009) Microfinance et services non financiers: Mariage impossible. Prorarco , N°3 septembre 2009.
Guitiérrez-Nieto, B., Serrano-Cinca, C. and Molinero, M. (2009) Social efficiency in microfinance institutions. Journal of the Operational Research Society, Vol. 60, pp. 104-119.
Guitiérrez-Nieto, B., Serrano-Cinca, C. and Molinero, M. (2007) Microfinance institution and efficiency. The international journal of Management Science, Omega, Vol.35, pp. 131-142.
Haq, M., Skully, M. and Pathan, S. (2010) Efficiency of Microfinance Institutions: A Data envelopment analysis", Asia-Pacific Financial Markets, Vol. 17, pp. 63-97.
Hermes, N., Lensink, R. and Meesters, A. (2009) Outreach and efficiency of microfinance institutions. World Development, 39(6), pp. 938-948.
Lafourcade, A.L., Isern, I., Mwangi, P. and Brown, M. (2005) Overview of the Outreach and Financial Performance of Microfinance Institutions in Africa. MIX, pp. 1-20.
Lapenu, C., Konini, Z. and Razakharivelo, Ch. (2009) Evaluation de la performance sociale: les enjeux d'une finance responsable. Revue Tiers Monde, N°197, pp. 37-54.
MMW (2010) MIX Microfinance World: 2010 Arab Microfinance Analysis and Benchmarking Report. Sanabel and CGAP, pp. 1-23.
MMW (2009) Arab Microfinance Analysis and Benchmarking Report. With the cooperation of MIX, Sanabel and CGAP, pp. 1-23.
MMW (2003) Benchmarking Arab microfinance: A report from the Microfinance Information Exchange. With the cooperation of MIX, Sanabel and CGAP, pp. 1-12.
Simar, L. (2003) Detecting outliers in frontier models: a simple approach. Journal of Productivity Analysis, 20(3), pp. 391–424.
Morduch, J. (1999) The role of subsidies in microfinance: Evidence from the Grameen Bank. Journal of Development Economics, Vol. 60, pp. 229–248.
Nghiem, H., Coelli, T. and Rao, D. S. P. (2006) The efficiency of microfinance in Vietnam: Evidence from NGO schemes in the north and the central regions. International Journal of Environmental, Cultural, Economic and Social Sustainability, 2(5), pp. 71-78.
Omri, W. and Chkoundali, R. (2011) The convergence between outreach and financial performance in Mediterranean MFIs: A panel data analysis. Transition studies review, Mediterranean and Middle East Papers , 18(1), pp. 149-163.
Simar, L. and Wilson, P. W. (1998) Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. Management Science, 44(1), pp. 49-61.
Simar, L. and Wilson, P. W. (2000) Statistical inference in nonparametric frontier models: the state of the art. Journal of Productivity Analysis, 13(1), pp. 49–78.
Simar, L. and Wilson, P. W. (2002) Non-parametric tests of returns to scale. European Journal of Operational Research, Elsevier, 139(1), pp. 115-132.
Simar, L. and Wilson, P. W. (2008), Statistical inference in nonparametric frontier models: recent developments and perspectives, In: H. Fried, C.A.K. Lovell and S.S. Schmidt (eds), The measurement of productive efficiency, (Oxford University Press), 2nd ed., chap 4.

Shephard, R.W. (1970) Theory of Cost and Production Function, (Princeton University Press).

Wilson, P. W. (1993) Detecting outliers in deterministic nonparametric frontier models with multiple outputs. Journal of Business and Economics Statistics, 11(3), pp. 319–323.
Wilson, P. W. (2008) FEAR 1.0: A software package for frontier efficiency analysis with R. Socio-Economic Planning Sciences, Vol.42, pp. 247–254.
Yaron, J. (1994) What makes rural finance institutions successful? The World Bank Research Observer, 9(1), pp. 49-70.

Appendix

Table1: Summery of MFIs efficiency studies

Authors	Inputs	Outputs	Method
Lafourcade and al. (2005)	Standard industry performance indicators: outreach (breadth and depth), financial structure, financial performance, efficiency and productivity, and portfolio quality.		Ratio analyses
Nghiem and al. (2006)	1. Labour cost 2. Non-labour costs (Administrative expense)	1. Number of savers 2. Number of borrowers 3. Number of groups	DEA [11], and a second stage Tobit regression
Gutiérrez-Nieto and al. (2007)	1. Credit officers 2. Operating expenses	1. Interest and fee income 2. Gross loan portfolio 3. Number of loans outstanding	DEA and *Principal Component Analysis* (PCA)
Cornée(2007)	1. Total Assets 2. Total Number of Employee	1. Return on assets (ROA) 2. Number of borrowers × percentage of female	DEA (CCR and BCC)
Ben Soltane (2008)	1. Number of employee(staff) 2. Total Assets	1. ROA 2. Number of borrowers × percentage of female	DEA (CCR and BCC)
Gutiérrez-Nieto and al.(2009)	1. Total assets 2. Operating costs 3. Number of employees	1. Number of active women borrowers 2. Indicator of benefit to the poorest 3. Gross loan portfolio(GLP) 4. Financial revenue	DEA (CCR)
Haq and al. (2010)	Production approach: 1. Labor 2. Cost per borrower 3. Cost per saver	1. Number of borrowers per staff 2. Number of savers per staff member	Two stages analysis: -DEA(CCR and BCC) - Tobit model
	Intermediation approach: 1. Total number of stuffs 2. Operating/administrative expansions	1. Gross loan portfolio 2.Total savings	

Table 3: Inputs and outputs descriptive statistic

Year	2006			2007			2008			2009		
	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median
Inputs												
TA	17415489	40180448	5009172	25329744	60180749	5782480	26829127	59589239	5398648	28082179	59110393	5941435
OEX	5063409	24713964	597765	5658089	26977183	846655	7761102	38679352	925413	7843352	40878451	1272223
NE	262	549	73	296	641	88	319	643	98	323	775	98
Outputs												
FR	11082423	57473194	972573	10978153	53526309	992041	12881931	61021550	1261840	12879950	62453183	1646177
POV	33494	69670	7723	40876	89260	8711	41065	79903	10691	39569	74750	10890

Source: Authors' elaboration

[11] DEA is compared with Parametric Linear Programming (PLP) and Stochastic Frontier Analysis(SFA).

Table 4: Outlier detection: Peer-count Index, Super-efficiency and Wilson (1993)

Year	Peer count Index		Super-efficiency		Wilson
2006	Aden	2	DEF	144,185	ABA
	Al Tadamun	32	Al Tadamun	7,654	Al Amana
	DEF	32	PARC	1,501	ASBA
	FMFI Syria	9	IDDA	1,258	DEF
	IDDA	14	FMFI Syria	1,108	FBPMC
	MFW	5	NMF	1,030	FONDEP
	PARC	1	Aden	1,005	SBACD
					Zakoura
2007	ABWA	4	DEF	7,995	ABA
	Al Awael	18	Al Majmoua	6,690	Al Amana
	Al Majmoua	22	Al Awael	1,942	Al Majmoua
	Al Tadamun	13	CEOSS	1,727	Al Rafah Bank
	CEOSS	31	ABWA	1,481	ASBA
	DEF	25	Al Tadamun	1,251	DEF
	Zakoura	28	Zakoura	1,021	FBPMC
					FONDEP
					SBACD
					Zakoura
2008	Al Awael	16	IDDA	20,472	Al Amana
	Al Majmoua	32	DEF	7,265	Al Majmoua
	Al Tadamun	51	Al Majmoua	6,230	Al Rafah Bank
	DEF	26	Al Awael	1,637	ASBA
	IDDA	19	Al Tadamun	1,360	DEF
					FBPMC
					Zakoura
2009	Al Awael	18	DEF	9,069	Al Amana
	Al Majmoua	38	Al Majmoua	3,686	Al Majmoua
	Al Tadamun	15	Al Awael	3,405	Al Rafah Bank
	Azal	9	Azal	2,151	ASBA
	CEOSS	48	CEOSS	1,251	DEF
	DEF	37	Al Tadamun	1,207	FBPMC
	IDDA	9	IDDA	1,035	Zakoura

Source: Authors' elaboration