Non-Parametric, Unconditional Quantile Estimation of Efficiency in Microfinance Institutions

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Abstract—We apply the non-parametric, unconditional, hyperbolic order-α quantile estimator to appraise the relative efficiency of Microfinance Institutions in Africa in terms of outreach. Our purpose is to verify if these institutions, which must constantly try to strike a compromise between their social role and financial sustainability are operationally efficient.

Using data on African MFIs extracted from the Microfinance Information eXchange (MIX) database and covering the 2004 to 2006 periods, we find that more efficient MFIs are also the most profitable. This result is in line with the view that social performance is not in contradiction with the pursuit of excellent financial performance. Our results also show that large MFIs in terms of asset and those charging the highest fees are not necessarily the most efficient.

Keywords—Data envelopment analysis, microfinance institutions, quantile estimation of efficiency, social and financial performance.

I. INTRODUCTION

THE financial liberalization policies of the eighties adopted by developing and emerging countries may have helped improve micro-economic and banking environments in some cases, but they generally produced disastrous results, at least from a social viewpoint [1]. Indeed, these policies have mainly resulted in an almost total disappearance of development banks and a segmentation of the credit market [2]. The consequence is that, in the least-developed countries, between 70% to 80% of the population, principally the low-income households, do not have any access to banking services [3], [4].

Microfinance institutions (MFI) have since grown in popularity as an alternative banking institution to provide saving and loan services to low-income people excluded from conventional financial institutions [5]. In the same vein, [6] argue that microfinance contributes toward improving the well-being of the poor. Some authors [7], [8] instead insist on the importance of microfinance in the development of the population. Far from being a form of charity, microfinance is primarily a way of providing low-income households with the chance of benefiting from the same services that all the others have. It thus complements the financial and banking landscape. Furthermore, authors like [8] stress that if appropriate procedures were followed, loans within the sector

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would not, in fact, be as risky as some would like to have it believed. Indeed, if microfinance has of late turned out to be successful, this is mainly a result of constant improvement in its system of loans. The strategy has been aimed at reducing the costs of unguaranteed small loans by increasing their volume, and, at the same time, ensuring high reimbursement rates. MFIs have thus become a central tool in the fight against financial exclusion, and their number has continued to increase, going above 10,000 in 2005 versus fewer than 5,000 in 2001 [9]. Despite this surge, many MFIs find it hard to attain financial independence, and so barely survive on subsidies from different international organizations. However, as [10] underscores, these subsidies have a long history in the developing countries, but they have never produced long-lasting positive results. Nevertheless, it is important to identify factors likely to influence MFI performance if only because of the presumed role they play in the fight against poverty, at least against financial exclusion. The central issue is therefore to know whether MFIs are performing well, and whether they can last autonomously in the long run. This issue requires us to tackle the following questions: 1) How can the performance of an MFI be measured? 2) What are the factors that affect performance? 3) Does MFI social performance contradict their financial sustainability? The idea is to identify efficiency drivers in order to formulate strategies for improvement as well as for the survival of MFIs. These different points are the subject of this study.

Currently, most studies on the performance of MFIs, e.g. [11], [12] are based on financial ratios identical to those used to measure performances in banking. However, ratio analysis assumes linearity and a constant return to scale, and cannot adequately capture the multidimensional aspects of banking activities and decisions, and, by extension, those of MFIs [13] [14]. Therefore, several authors, e.g. [15], [14] suggest non-parametric methods, especially Data Envelopment Analysis (DEA), as an alternative for assessing the performance of financial institutions. Quite recently, this method was applied to MFIs in Latin America by [16], [17]. These authors show that efficiency varies according to country and the status of the MFI: non-governmental organization (NGO) versus non-NGO. They also conclude that DEA provides more information than ratio analysis. However, despite its flexibility in a multi-input, multi-output environment like that of financial institutions, DEA has some major drawbacks that need to be addressed. Indeed, DEA estimates can be extremely sensitive to outliers in the data [18], [19]. Furthermore, [20] pointed out that DEA estimators, like some other non-parametric estimators, suffer from the curse of dimensionality.

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In other words, the convergence rates to the true value are slow and the number of observations required to obtain meaningful estimates grows dramatically with dimensionality (number of inputs and outputs).

In this study, we also apply a non-parametric method to assess the performance of MFIs in African countries. However, while extending the works of [16] on MFIs of Africa, our study goes further and differs from theirs in several aspects:

1. From the methodological standpoint, we use the non-parametric unconditional quantile estimation method (HQ estimator), thus avoiding many of the known drawbacks of the DEA estimator. Indeed, this estimator, recently put forward by [20], [21], overcomes the curse of the dimensionality problem, and is robust to outliers. Besides, it does not require one to decide whether to measure efficiency in the input or the output direction. This issue is important, especially in the context of MFIs. On the one hand, it can be argued that MFIs have very limited resources and probably operate below their optimal size, since they are generally of small size, particularly when compared with traditional banking institutions. In this case, the objective would be to produce the maximum outputs from available resources. On the other hand, MFIs are, for the most part, financially unprofitable and dependent on subsidies and other grants. Therefore, it may appear reasonable, at least on the grounds of financial sustainability, for one to assume that they must seek to minimize their inputs for the same level of outputs. The HQ estimator used in this study enables estimation of efficiency by simultaneous adjustment of inputs and outputs along a hyperbolic path, rather than in either strictly an input or an output direction.

2. It is also worth noting that [16] study concern only 30 MFIs. As pointed out by [22], applying DEA with a sample size as small is likely to produce meaningless results in a statistical sense due to the curse of dimensionality problem. With sample size of more than 140 yearly observations as in this study, the curse of dimensionality will be still probably an issue with DEA estimator.

3. Furthermore, this study contributes to the debate on the tradeoff between the MFI social role and their financial sustainability by relating the efficiency estimates to profitability variables like return on asset.

Using data on African MFIs extracted from the Microfinance Information eXchange (MIX) database and covering the 2004 to 2006 periods, we find that more efficient MFIs are also the most profitable. Our results show no evidence of trade-off between outreach and financial sustainability, which is in line with the view that social performance does not contradict the pursuit of excellent financial performance. Our results, however, show that large MFIs in terms of assets and those asking for the highest financial revenues on loans (interest rates and fees) are not necessarily the most efficient.

The rest of this paper is structured as follows. Section II presents the methods applied in this study to measure the efficiency of African MFIs and describes our data. In Section III, we discuss the variables. We analyze the results in Section IV. Our concluding remarks are presented in Section V.

II. METHODOLOGY

We estimate the technical efficiency of Microfinance Institutions (MFIs) in Africa using the non-parametric, unconditional, hyperbolic order-α quantile estimator (HQ) put forward by [20], [21] along with other more frequently used non-parametric estimators, such as the Data Envelopment Analysis (DEA) and the Free Disposal Hull (FDH).

Non-parametric methods involve estimating a production set at time t, $\mathcal{P}^t \equiv \{(x,y)|x \text{ can produce } y \text{ at time } t\}$, which represents the set of feasible combinations of p input quantities (x), $x \in R_+^p$ and q output quantities (y), $y \in R_+^q$ at a given point in time. We dropped the time subscript for the remainder of this paper to improve readability.

The efficiency of a decision-making unit (DMU), an MFI in our case, is defined relative to some benchmark that is the upper boundary of $\mathcal{P}$ or full production frontier, denoted $\mathcal{P}^\theta$, for DEA and FDH estimators, or partial production frontier $\mathcal{P}_\alpha^\theta$ for the HQ estimator, where $\alpha \in (0,1]$. If $\alpha=1$, then $\mathcal{P}^\theta = \mathcal{P}_\alpha^\theta$. Relative efficiency or inefficiency of a DMU$_0$ with x$_0$ input and y$_0$ output quantities is usually measured as distance relative to the benchmark. Reference [23] defined input and output distance functions given by

$$\theta(x_0, y_0 \mid \mathcal{P}) \equiv \sup\{\theta > 0 | (\theta^{-1}x, y) \in \mathcal{P}\} \quad (1)$$

and

$$\lambda(x_0, y_0 \mid \mathcal{P}) \equiv \inf\{\lambda > 0 | (x, \lambda^{-1}y) \in \mathcal{P}\}, \quad (2)$$

respectively. The input distance function $\theta(x_0, y_0 \mid \mathcal{P})$ measures distance from (x_0, y_0) to $\mathcal{P}^\theta$ in a direction orthogonal to y, while the output distance function $\lambda(x_0, y_0 \mid \mathcal{P})$ measures distance from the same point to $\mathcal{P}^\theta$ in a direction orthogonal to x. Frontiers in input or output direction could be different thus impacting the measured efficiency of the DMU. As an alternative, [24] propose the hyperbolic graph efficiency measurement

$$\gamma(x, y| \mathcal{P}) \equiv \sup\{\gamma > 0 | (\gamma^{-1}x, \gamma y) \in \mathcal{P}\} \quad (3)$$

which provides distance from the fixed point (x_0, y_0) to $\mathcal{P}^\theta$ along the hyperbolic path $(\gamma^{-1}x, \gamma y), \gamma \in R_{++}^1$. By construction, $\theta(x, y) \geq 1$, $\lambda(x, y) \leq 1$, and $\gamma(x, y) \leq 1$ for $(x, y) \in \mathcal{P}$.

References [25], [26] provide a probabilistic formulation of efficiency concepts. These authors note that assuming that the sample observations S$_n$ are realizations of identically, independently distributed random variables with probability density function f(x,y) with support over $\mathcal{P}$ implies a probability function given by H(x$_0$, y$_0$) = Pr(x $\leq$ x$_0$, y $\geq$ y$_0$).

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This function gives the probability of drawing an observation from f(x, y) that weakly dominates the DMU operating at $(x_0, y_0) \in \mathcal{P}$. Based on H(.,.), the distance functions described in (1), (2), (3) can be written as

$$\theta(x_0, y_0 \mid \mathcal{P}) \equiv sup\ \{\theta > 0 | H(\theta^{-1}x, y) > 0\} \qquad (4)$$

$$\lambda(x_0, y_0 \mid \mathcal{P}) \equiv inf\ \{\lambda > 0 | H(x, \lambda^{-1}y) > 0\}, \qquad (5)$$

$$\gamma(x_0, y_0 \mid \mathcal{P}) \equiv sup\ \{\gamma > 0 | H(\gamma^{-1}x, \gamma y) > 0\} \qquad (6)$$

Unfortunately, $\mathcal{P}$ or $\mathcal{P}^{\theta}$ and therefore the distance functions are unknown and must be estimated from a set $S_n = \{x_i, y_i\}_{i=1}^{n}$ of observed input/output combinations.

DEA or FDH involve the estimation of the distance function relative to the full production frontier or benchmark. Instead, the HQ estimator considers a partial frontier as benchmark ($a \leq 1$). Below we describe the FDH, DEA and HQ estimators following [20], [21], [27].

A. FDH and DEA Estimators

The FDH estimator proposed by [28] can be defined as the smallest free disposal set containing all observations in the sample (S_n) of production units, i.e.,

$$\widehat{\mathcal{P}}_{FDH}(S_n) = \cup_{(x_i, y_i) \in S_n} \{(x, y) \in R_+^{p+q} | y \leq y_i, x \geq x_i\} \qquad (7)$$

The DEA estimator initiated by [29] and popularized as linear programming estimator by [30] assumes the convexity of the free disposal set and can be written:

$$\widehat{\mathcal{P}}_{DEA}(S_n) = \quad \{(x, y) \in R_+^{p+q} | y \leq \sum_{i=1}^{n} \delta_i y_i, x \geq \sum_{i=1}^{n} \delta_i x_i, \sum_{i=1}^{n} \delta_i = 1, \delta_i \geq 0 \ \forall\ i = 1, \dots, n\} \qquad (8)$$

This estimator allows for variable returns to scale. Constant return of scale can be obtained by dropping the constraint $\sum_{i=1}^{n} \delta_i = 1$, in (8).

Assuming $Pr(x_i, y_i) \in \mathcal{P}) = 1\ \forall\ i = 1, \dots, n$, the resulting FDH estimators of the efficiency scores can be obtained by replacing $\mathcal{P}$ by $\hat{P}_{FDH}(S_n)$ in the definition of the efficiency scores in (1), (2) and (3) or in (4), (5), and (6). Similarly, DEA estimators are obtained by plugging $\widehat{\mathcal{P}}_{DEA}(S_n)$ in place of $\mathcal{P}$ to obtain $\hat{\theta}_{FDH}(S_n), \hat{\lambda}_{FDH}(S_n)$ or $(\hat{\gamma}_{FDH}(S_n))$.

B. HQ Estimator

The HQ estimator is obtained by replacing $H(\cdot, \cdot)$ in (6) by its empirical analog, i.e

$$\hat{H}(x_0, y_0 | S_n) = \frac{1}{n} \sum_{i=1}^{n} I(x_i \leq x_0, y_i \geq y_0 | (x_i, y_i) \in S_n) \quad (9)$$

where $I(\cdot)$ denotes the indicator function. Then an estimator of $\gamma_\alpha(x, y)$ is obtained by replacing $H(\cdot, \cdot)$ by $\hat{H}(\cdot, \cdot | S_n)$ to obtain

$$\hat{\gamma}_\alpha(x, y) = sup\ \{\gamma > 0 | \hat{H}(\gamma^{-1}\boldsymbol{x}, \gamma \boldsymbol{y} | S_n) > (1 - \alpha)\} \qquad (10)$$

The hyperbolic FDH, DEA and HQ estimators are used to examine the technical efficiency of African MFI from 2004 to 2006.

C. Sample Characterized

The data are drawn from the MIX database. The sample consists of 519 MFIs operating in Africa, including 142 observations in 2004, 174 in 2005, and 202 in 2006. We consider only African MFIs to ensure certain homogeneity of the data. Indeed, studies [31], [32] show that socio-economic environment influence the performance of MFIs. On this point, according to statistics collected by the United Nations [33], the per capita gross national income (GNI) is on average $5,587 in Latin America and the Caribbean, $3,283 in Asia and $1,198 in Africa. In the African countries, where our sampled MFIs operate, the GNI is on average $558.37 in 2004, $653.36 in 2005 and $704.36 in 2006 (see Table I). Moreover, as reported by [32], MFIs located in Africa are smaller in terms of gross loan portfolio compared with those in Asia (south and east) or from Latin America. For example, using data extracted from MIX as we do, the average gross loan and total saving in [32] sample is in 2004 respectively 25 and 21 million dollars in Africa compared with 301 and 484 in East Asia, 60 and 28 in South Asia and 69 and 61 in Latin America. However, as can be seen from Table I, even though they originate from the same region, our sampled MFIs remain somewhat heterogeneous at least in regard of some of their characteristics. For example, the average total asset is roughly $16 million in 2006, with a median of $2 million and a standard deviation of $42 million. As for the gross loan portfolio, in 2006, the figures were respectively (mean, median, standard deviation) $9, $1.5 and $24 million. Three other variables shown in Table I as characterizing the sample are the average loan balance per borrower, the financial revenue over the loan portfolio (FinRev) and the return on assets (ROA).

FinRev represents the percentage of interest and other financing fees the MFI charges to its customers in return for its services and mostly reflects the borrowing cost from an MFI. As we can see from Table I, FinRev was on average 40.51%, 47.53% and 44.23% in 2004, 2005 and 2006 respectively. Other authors, including [34], [35], also observed and criticized this practice of high lending rate as incompatible with the social objective that MFIs are expected to pursue. However, despite this high percentage of lending revenues relative to the loan portfolio, the numbers in Table I show that most MFIs are unprofitable, with the ROA, which measures the financial performance of the MFI, being negative on average over the three years of our study: -1.6 in 2004, -0.9 in 2005 and -1.3 in 2006. Nevertheless, the median ROA is positive, indicating that more than half of the MFI are still profitable.

We provide in the next section some more information on the sampled MFIs along with the justification, and the description of the inputs and outputs used in this study.

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TABLE I
DESCRIPTIVE STATISTICS OF VARIABLES CHARACTERIZING THE SAMPLE

Variables	Gross National Income (GNI)	Total assets (000)	Gross loan portfolio (000)	Average loan balance per borrower	Return on assets (%)	FINREV[a] (%)
2004 (Number of observations=142)						
Mean	558.37	10,148.17	6,554.83	419.79	-1.60%	40.51%
Median	380.70	2,072.88	1,275.09	194.00	1.36%	31.81%
Std	589.29	18,730.74	11,851.79	630.59	11.91%	25.87%
Min	89.81	50.85	25.45	42.00	-50.50%	3.31%
Max	3,631.39	103,036.37	51,470.10	5,086.00	22.63%	186.56%
2005 (Number of observations=174)						
Mean	653.36	13,528.88	7,700.49	440.71	-0.09%	47.53%
Median	442.18	2,311.14	1,373.74	184.50	0.89%	35.15%
Std	744.93	30,344.17	15,898.23	686.11	12.42%	45.59%
Min	89.94	39.54	0.00	15.00	-81.98%	0.00%
Max	4,810.38	202,799.35	86,546.35	4,335.00	50.32%	407.68%
2006 (Number of observations=202)						
Mean	704.36	16,158.64	9,251.72	578.94	-1.31%	44.23%
Median	508.20	2,320.81	1,500.00	217.00	1.34%	36.34%
Std	784.18	42,472.86	24,017.93	1,705.99	11.97%	30.49%
Min	99.93	2.59	0.00	11.00	-67.54%	2.07%
Max	5,420.88	303,972.54	219,106.02	22,252.00	31.36%	199.51%

a. FINREV= Financial revenue divided by the Gross loan portfolio

III. SELECTING THE OUTPUTS AND INPUTS

The choice of suitable outputs and inputs is probably the most important task for a successful performance assessment, because it is this matrix of the variables, which fixes the comparison context [36]. Within the banking sector, the debate on the choice between the production and the intermediation approach is an ongoing one. Reference [37] provides in-depth discussion on this debate. On the one hand, the production approach, where financial institutions are production units using capital and labor as inputs to supply services in terms of deposits and loans. On the other hand, the intermediation approach, where they are financial intermediaries between depositors and borrowers. Therefore, we should also consider the magnitude of the production. In the production approach, the number of depositors is an output, whereas the amount of deposits is an input in the intermediation approach. In both cases, labor and capital are usually considered as inputs.

Interestingly, in the microfinance literature, most studies adopt the production approach precisely because it does not take into account the amount involved. Indeed, as pointed out by [16], many MFIs do not even collect deposits—an important aspect of the intermediation model—but rather receive donations and subsidies. Therefore, the production model is deemed more suitable to assess the efficiency of MFIs, since the emphasis in these institutions is in the granting of loans rather than in the collection of deposits.

The diversity of the sampled MFIs that we reported earlier is another reason for adopting the production approach, which essentially implies a comparison in terms of numbers (e.g., the number of borrowers), rather than gross amounts (e.g., the amount of loan portfolio). For example, the production approach would favor an MFI serving many borrowers with small loans, all things being equal, as more efficient than an MFI serving one big customer with a larger loan amount than those granted by the first MFI.

For all the above-mentioned motives, we also opt for the production approach in this study and use as outputs: 1) the number of borrowers; and 2) the number of depositors. The inputs are: 1) Labor; 2) Physical assets; and 3) Operating expenses. We justify the choice of these variables below and provide summary statistics in Table II.

A. Outputs

The number of depositors and the number of borrowers are often used as outputs in several studies, which apply DEA with the production approach to the banking sector [38]-[40], [36]. These variables are also used in the microfinance literature as outreach measures [41], [42], that is the ability of the MFI to serve as many people as possible, in particular, those who were previously denied access to formal financial services. These variables can then be considered as appropriate to assess the efficiency of MFIs, especially those that consider social performance instead of profit as their main objective. The question of interest is, regardless of wages and magnitude of loans or deposits involved, which MFIs serve more customers?

B. Inputs

We use three inputs: 1) labor; 2) physical assets as a proxy for capital; and 3) operating expenses. Labor refers to the workforce measured as the total number of employees. Physical assets represent fixed assets (land and buildings) and other tangible assets. Following [37], [16], [17], we also use operating expenses as input, that is all necessary costs to service customers, including all the administrative and salary expenses, depreciation and board fees.

Following [43], we normalize the variables, physical assets and operating expenses, expressed in dollars, by the country

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GNI. Indeed, since our study involves a cross-country analysis, by doing so, all our variables are more comparable, as if they are all expressed in number, and thus the units we aim to compare. We also avoid situations where an MFI would be considered efficient only because it operates in a low-cost country. Indeed, a one-dollar expense in one country may not necessarily be equivalent in another country, even if the two countries are located in the same region.

TABLE II
DESCRIPTIVE STATISTICS OF THE INPUTS AND THE OUTPUTS

Variables	Inputs			Outputs	
	Input 1 Physical Asset[a]/GNI[b]	Input 2 Operating expense/GNI[b]	Input 3 Number of personnel	Output 1 Number of active borrowers (000)	Output 2 Number of depositors (000)
2004 (Number of observations=142)					
Mean	10,050.58	3,618.59	149.32	24.16	29.73
Median	1,821.99	1,155.59	66.00	8.75	2.26
Std	26,128.84	6,937.65	218.90	49.50	79.98
Min	15.81	15.03	2.00	0.07	0.00
Max	224,676.46	65,275.74	1,670.00	351.16	429.54
2005 (Number of observations=174)					
Mean	12,332.23	3,727.61	173.99	26.77	26.00
Median	2,258.68	1,159.73	66.00	7.47	3.11
Std	38,879.67	7,577.31	298.13	60.78	70.21
Min	16.92	24.22	3.00	0.00	0.00
Max	378,490.84	68,065.29	1,915.00	434.81	496.54
2006 (Number of observations=202)					
Mean	12,444.62	4,070.76	178.14	28.28	35.65
Median	1,890.27	995.47	62.50	7.46	4.33
Std	41,240.30	8,894.06	324.63	67.98	124.65
Min	0.34	1.11	2.00	0.00	0.00
Max	379,317.76	73,196.30	2,129.00	536.80	1,090.00

[a.] Physical asset = Total assets minus Gross loan portfolio. [b.] GNI= Gross National Income

IV. RESULTS

Table III presents our estimates of MFI efficiency scores using hyperbolic DEA, FDH and HQ estimators obtained with the FEAR library [27]. The reported results are so that increasing values of efficiency estimates correspond to increasing efficiency.

A. Technical Efficiency of MFI

The DEA estimates, hyperbolic orientation and variable returns of scale, suggest a fairly high level of technical efficiency among MFIs. Indeed, as shown in Table III, the mean efficiency scores range from 0.647 to 0.671 for an average of 0.659 in the 2004 to 2006 period. Following [18], we also compute the bias corrected DEA efficiency scores. The results are basically similar ranging from 0.583 in 2004, 0.574 in 2005 and 0.558 in 2006. The 0.659 average efficiency indicates an efficiency of 1 MFI out of 1.517 (1/0.659). We obtain higher efficiency estimates using the FDH estimator. Indeed, the efficiency scores range from 0.847 to 0.882 with an average of 0.864 over the period or more than 86% efficiency level. Considering the difference between the FDH and DEA estimators are based only on the assumption of

convexity, these results indicate that over 20% (86% - 66%) of the inefficiencies identified with the DEA estimator are based on the assumption of convexity.

We also use the HQ estimator to obtain estimates of efficiency for every MFI in each year. As for the DEA and FDH estimators, we obtain a relatively high level of efficiency using the HQ estimator. Indeed, the median (average) efficiency with α=95% varies from 1.797 (2.195) to 2.004 (2.424). The median (average) is 1.910 (2.423) over the period indicating that the median MFI uses 52.3% (1/1.91) of the inputs, but generates almost twice (1.91%) the outputs of the MFI located on the 95% efficiency frontier. These findings are consistent with those obtained with the FDH estimator, which as we know, corresponds to the 100% efficient frontier version of the HQ estimator (α = 100%). Indeed, we observe that over 80% of MFI (252 out of 518) are located on the FDH frontier (efficiency score = 1).

Logically, we observe as well that more MFI (over 92% or 478 out of 518) are located on the 95% HQ partial frontier or beyond.

Overall, we can conclude that African MFIs are quite relatively efficient, at least when compared with one another, even if the estimated efficiency of the MFIs obtained using HQ estimator exhibit considerable variability. For example, in 2004, our estimations show the most efficient MFI used just 6.9% (1/14.51) of the input amounts and produced over 14 times (14.51) more output than an MFI located on the 95% quantile frontier. The least efficient MFI in 2004, by contrast, used 248.1% (1/0.403) of the input and produced 40.3% of the output produced by an MFI on the 95% quantile frontier. The results are similar in 2005 and 2006. The most efficient MFI use only 11.7% (1/8.58) in 2005 and 3.4% (1/29.038) in 2006 of inputs amounts and produce 8.5 times (2005) and 29.038 times (2006) more outputs than an MFI located on the 95% quantile frontier. Alternatively, the least efficient MFI use more than double (1/0.48 in 2005 and 1/0.47 in 2006) of the inputs and produce only 48% (2005) and 47% (2006) of the outputs generated by an MFI located on the 95% quantile frontier.

Of course, the specific HQ estimates depend on the choice of α, which determines the location of the unique α–quantile frontier. However, our results are qualitatively robust with value of α=0.90 or 0.85. Indeed, as shown in Table IV for each of the three years periods covered in this study, there is a high spearman rank correlation, more than 95%, between the HQ efficiency estimates for α equal to 0.85, 0.90 or 0.95.

The correlations between the DEA and FDH scores and between the DEA or FDH and the HQ efficiency estimates are much lower ranging from 65% to 88%. However, the general indication is that MFIs found to be least efficient using either the DEA or FDH estimators correspond to MFIs identified as least efficient applying the HQ estimator. This result reveals that there is quite a good correspondence between the rankings of MFIs by HQ, DEA and FDH estimators. However, the relatively small size of our samples casts some doubts on estimates of technical efficiency using DEA or FDH estimator because of the curse of dimensionality and their slow

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convergence rates. As pointed out earlier, the HQ estimator has a root-n convergence rate when used to estimate distance to a partial frontier and does not impose convexity in contrast to DEA. Moreover, unlike DEA and FDH, it provides full ordering of MFIs in terms of efficiency. Therefore, in the next section, we explore the factors that may affect the performance of MFI based only on HQ estimates.

TABLE III
DESCRIPTIVE STATISTICS OF EFFICIENCY SCORES

	DEA	BIAS[a]	FDH	HQ (α=0.85)	HQ (α=0.90)	HQ (α=0.95)
2004 (Number of observations=142)						
Mean	1.736	1.957	1.229	0.323	0.416	0.576
Median	1.572	1.727	1.000	0.278	0.359	0.499
Sd	0.851	0.913	0.484	0.238	0.276	0.343
Min	1.000	1.139	1.000	0.016	0.036	0.069
Max	6.349	7.247	3.943	1.558	1.861	2.481
2005 (Number of observations=174)						
Mean	1.674	1.908	1.213	0.315	0.406	0.576
Median	1.567	1.758	1.056	0.295	0.398	0.557
Sd	0.605	0.644	0.342	0.185	0.214	0.276
Min	1.000	1.140	1.000	0.034	0.050	0.117
Max	4.508	4.842	3.000	1.161	1.333	2.096
2006 (Number of observations=202)						
Mean	1.812	2.070	1.290	0.330	0.422	0.580
Median	1.600	1.810	1.044	0.280	0.362	0.517
Sd	0.882	0.981	0.508	0.221	0.271	0.338
Min	1.000	1.125	1.000	0.014	0.019	0.034
Max	6.649	7.697	3.699	1.415	1.843	2.150

[a] Bias-corrected estimates of DEA efficiency scores following [18] bootstrap approach

TABLE IV
SPEARMAN RANK CORRELATION OF EFFICIENCY SCORES

	DEA	BIAIS[a]	FDH	HQ (α=0.85)	HQ (α=0.90)	HQ (α=0.95)
2004 (Number of observations=142)						
DEA	1.000	0.983	0.753	0.820	0.850	0.877
BIAIS		1.000	0.755	0.758	0.787	0.823
FDH			1.000	0.554	0.589	0.670
HQ(α=0.85)				1.000	0.984	0.925
HQ(α=0.90)					1.000	0.955
HQ(α=0.95)						1.000
2005 (Number of observations=174)						
DEA	1.000	0.985	0.815	0.758	0.801	0.867
BIAIS		1.000	0.805	0.686	0.736	0.814
FDH			1.000	0.666	0.700	0.759
HQ(α=0.85)				1.000	0.982	0.932
HQ(α=0.90)					1.000	0.958
HQ(α=0.95)						1.000
2006 (Number of observations=202)						
DEA	1.000	0.992	0.815	0.675	0.741	0.800
BIAIS		1.000	0.813	0.648	0.715	0.777
FDH			1.000	0.733	0.779	0.825
HQ(α=0.85)				1.000	0.984	0.949
HQ(α=0.90)					1.000	0.969
HQ(α=0.95)						1.000

[a] Bias-corrected estimates of DEA efficiency scores following [18] bootstrap approach

B. Explaining the Efficiency Scores

We use a regression analysis in a second stage in an attempt to explain the variation in the efficiency scores measured in the first stage. Numerous authors, including [44]-[50], have also followed this two-stage procedure to investigate efficiency drivers. However, as pointed out by many authors [48]-[51], the efficiency scores obtained in the first-stage exhibit serial correlation, and are correlated with the explanatory variables used in the regression analysis. Therefore, estimates from standard regression analysis will be inconsistent and biased. To circumvent this problem, we estimate a truncated bootstrap regression following the procedure suggested by [50] as described below:

Considering a regression model, $\hat{\gamma}_i = \beta z_i + \varepsilon_i$, where $\hat{\gamma}_i$ represent the estimated efficiency scores, z_i a vector of explanatory variables, and β refers to a vector of parameters with some statistical noise ε_i,

1. use the maximum likelihood method to obtain estimates $\hat{\beta}$ of β as well as an estimate $\hat{\sigma}_\varepsilon$ of σ_ε in the truncated regression of $\hat{\gamma}_i$ on the independent variables, z_i.

2. repeat the next three steps (a, b and c) L times to obtain a set of bootstrap estimates. $A = \left\{ \left(\hat{\beta}^*, \hat{\sigma}_\varepsilon^* \right)_b \right\}_{b=1}^{L}$

a. For each i=1,…n, draw ε_i from the N(0, $\hat{\sigma}_\varepsilon^2$) distribution with left truncation at $(-\hat{\beta} z_i)$. Recall that in [23] distance function, HQ efficiency estimates are, by construction, greater than or equal to zero, while DEA estimates are greater than or equal to one. Consequently, we draw ε_i from the N(0, $\hat{\sigma}_\varepsilon^2$) distribution with left truncation at $(-\hat{\beta} z_i)$ rather than at $(1-\hat{\beta} z_i)$, as in previous studies that use DEA estimates as independent variable.

b. for each i=1,…n, compute $\gamma_i^* = \hat{\beta} z_i + \varepsilon_i$

c. use the maximum likelihood method to estimate the truncated regression of γ_i^* on z_i providing estimates $(\hat{\beta}^*, \hat{\sigma}_\varepsilon^*)$

3. use the bootstrap values in A and the original estimates $\hat{\beta}, \hat{\sigma}_\varepsilon$ to construct estimated confidence intervals for each element of β and for $\hat{\sigma}_\varepsilon$.

Our estimated specification for the regression is as follows and included some control variables, such as financial revenues, size, country GNI and location, likely to impact the performance of the MFI:

$$\hat{\gamma}_{i\,95\%} = \beta z_i + \varepsilon_i \; ; \tag{11}$$

$$\hat{\gamma}_{i\,95\%} = \beta_0 + \beta_1.ROA_i + \beta_2.FinRev_i + \beta_3.TOT_{ASSET_i} + \beta_4.D_{1_{GNI}} + \beta_5.D_{2_{GNI}} + \beta_6.D_{1\_Country} + \beta_7.D_{2\_Country} + \varepsilon_i$$

where $\hat{\gamma}_{i\,95\%}$ represents the 95% HQ efficiency score as estimated previously and representing the social performance of MFIs. ROA measures the financial performance of the MFI. As defined before, FinRev represents the cost of borrowing from an MFI. TOT_ASSET = Total assets, and is used as a proxy for the size of the MFI. One might expect a negative relationship between efficiency scores and the size of the MFI,

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at least if we are to believe authors like [52], fearing a diversion of MFIs of their social mission as it seeks more profitability. Indeed, the largest MFIs may prefer to have fewer loan and deposit accounts, but larger loans and deposits, thus abandoning their most needy customers.

$D_{1_{GNI}}$ and $D_{2_{GNI}}$ are dummy variables used to control for the wealth of the country where the MFI operates. $D_{1_{GNI}} = 1$ if the GNI of the country where the MFI operates is greater than or equal to the 67th percentile and zero otherwise. $D_{2_{GNI}} = 1$ if the GNI of the MFI home country is between the 33th and 67th percentile and zero otherwise. Let us not forget that the primary role of MFIs is to provide financial services to a population excluded from the traditional banking structure. Therefore, as our outputs essentially measure the outreach of MFIs, on the one hand, we can expect higher MFI activity and probably a higher efficiency score in the poorest countries, which may also have greater mutual assistance culture. On the other hand, MFIs from poor countries could be less efficient, because of a lack of technical resources and necessary expertise to expand operations to the widest possible customer base.

$D_{1\_Country}$ and $D_{2\_Country}$ represent MFI home country location and are also dummy variables. $D_{1\_Country} = 1$ if the MFI is from country in central or West Africa, and zero otherwise. $D_{2\_Country} = 1$ if the MFI is from North Africa and zero otherwise. These country location variables are included to check if the efficiency score is influenced by the cultural or socioeconomic environment of the country. We classify our samples into three regional groups. 1) The West and Central Africa. These are mainly French-speaking countries, former French colonies and with the CFA franc as a common currency. 2) South and East Africa. These are mainly English-speaking countries that joined to form the Southern African Development Community (SADC). However, they do not share a common currency like the Francophone African countries. 3) North Africa. This group includes countries situated north of the Sahara that are geographically closer to Europe. They can be called Arab Africa or White Africa in contrast to Black Africa designating sub-Saharan Africa. North African countries can also be categorized by their predominantly Muslim population, even if they share this characteristic with some black African countries like Mali and Senegal in West Africa.

The results of the regression analysis are presented in Table V. The estimated coefficients corresponding to $D_{1_{GNI}}$ et $D_{2_{GNI}}$ are both significant and positive implying that MFIs located in countries with high GNI are more efficient. One explanation could be that MFIs operating in very poor countries lack the technical resources essential to expand significantly their customer base.

The positive coefficients on the two country location variables, $D_{1\_Country}$ and $D_{2\_Country}$, suggest that MFIs located in South and East Africa are less efficient than those in other regions of Africa, though not to a significant degree in 2006. Our guess is that the culture of microfinance or social finance is less common in these, mostly Anglophone countries, which

are however closing the gap, hence the insignificant estimated coefficient in 2006, the last year of our study

TABLE V
TRUNCATED BOOTSTRAPPED SECOND-STAGE REGRESSION A(DEPENDENT VARIABLE: HQ (α=0.95))

	2004	2005	2006
	Coefficient (z-stat)	Coefficient (z-stat)	Coefficient (z-stat)
Constant	-0.165 (-0.64)	-0.286* (1.83)	-0.193 (-1.00)
Return on assets	0.796*** (3.58)	0.678*** (3.7)	0.577*** (2.99)
Total assets	-0.034** (-2.15)	-0.001 (-0.11)	-0.024** (-1.95)
FINREV	-0.304*** (-2.89)	-0.234** (2.09)	-0.342*** (-4.69)
D_GNI1	0.165*** (2.60)	0.132** (2.22)	0.174*** (2.68)
D_GNI2	0.125* (1.86)	0.105** (2.04)	0.105* (1.88)
D_PAYS1	0.172** (2.49)	0.153*** (3.11)	0.058 (1.14)
D_PAYS2	0.213* (1.99)	0.134* (1.82)	0.101 (1.09)
Adj R-squared	0.2198	0.1505	0.1832

[a] Total number of iterations = 2000. *, **, *** Indicate statistical significance at the 10%, 5% and 1% level respectively

The results reported in Table V also indicate an inverse relationship between total assets and the efficiency score, implying that an increase in size leads to a decrease in efficiency, though to an insignificant degree in 2005. More importantly, it can also be seen in Table V, that efficiency increases along with the ROA, but decrease with the financial revenue that the MFI collected from lending activities (FinRev). One interpretation is that MFIs charging a high interest rate and fees (FinRev) have relatively fewer borrowers, and, therefore, a lower efficiency score. By contrast, those who have a high ROA are more efficient. Looked at another way, one can conclude that, despite the additional risk of serving a somewhat riskier population excluded from the traditional system, MFIs charging a reasonable interest rate compensates for this shortfall by attracting a larger clientele, hence the higher ROA. These results also show implicitly that the default rate is not as high as one would expect from these presumably high-risk clienteles. These findings favor the idea put forward by some authors [53], [54] that the loans in the microfinance sectors are not always as risky and social performance is not necessarily antithetical to the financial profitability.

V. CONCLUSION

We have assessed the relative efficiency of African MFIs using data from the MIX database to obtain a sample totaling 519 observations covering the 2004 to 2006 period. In a second stage, we estimated a truncated regression using the bootstrap procedure suggested by [51] to explain the efficiency scores.

To the best of our knowledge, this article is the first application of the HQ estimator to evaluate the relative efficiency of MFIs. Unlike DEA and FDH estimates, the HQ estimator is not affected by the curse of dimensionality, and is robust to outliers [20], [21]. Moreover, as shown by [51], the truncated regression method with estimates obtained using a bootstrap procedure provides a more valid inference in regard to the fact the efficiency scores are serially correlated.

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Our results show that African MFIs have a fairly high level of relative efficiency, at least when compared with each other. The result of the second-stage regression reveals that the most profitable MFIs are also those that exhibit the highest efficiency score. By contrast, MFIs with high financial revenue (interest and fees) relative to loan portfolio have a lower efficiency score. These results are in line with the view of some authors as [53], [54] who argue that strong financial performance does not necessarily mean excellence in coverage of poor households while reaching the poorest is not in contradiction with the pursuit of excellent financial performance.

As future research, it would be interesting to extend this research to other geographic regions and to perform inter-regional comparisons. One could also compare the MFIs according to their legal status (NGOs, Cooperatives or Bank).

REFERENCES

[1] J. E. Stiglitz, *La grande désillusion*. Paris : Fayard, 2002.
[2] M. Robinson, "Addressing some keys questions on finance and poverty," Journal of International Development 8: 153-161, 1996.
[3] P. Honohan, "Household financial assets in the process of development," World Bank Policy Research Working Paper 3965, 2006.
[4] T. Beck, A. Demirguc-Kunt and M.S. Martinez Peria, "Reaching out: Access to and use of banking services across countries" Journal of Financial Economics 85: 234-266, 2007.
[5] M. Schreiner, "Scoring: The next breakthrough in microfinance?" Occasional Paper, Consultative Group to Assist the Poorest, Washington, D.C. 2002.
[6] M. Zeller and M. Sharma, "Many borrow, more save, and all insure: Implication for food and microfinance policy" Food policy 25: 143-167, 2000.
[7] B. A. DeAghion and J. Morduch, *The Economics of Microfinance*. MIT Press, 2005.
[8] G. Barboza and H. Barreto, "Learning by Association: Micro Credit in Chiapas. Contemporary Economic Policy," Mexico 24: 316-331, 2006.
[9] S. Boyé, J Hajdenberg and C. Poursat, *Le guide de la microfinance: Microcrédit et épargne pour le développement*. Edition d'Organisation. 2006.
[10] J. Morduch, "Sibling Rivalry in Africa," American Economic Review 90: 405-409, 2000.
[11] M. Tucker and G. Miles, "Financial performance of microfinance institutions: A comparison to performance of regional commercial banks by geographic region," Journal of Microfinance 6: 41-54. 2004.
[12] Koveos P and Randhawa D (2004). Financial service for the poor: assessing microfinance institutions. Managerial Finance 30: 70-95.
[13] A. D. Athanassopoulos and J. A. Ballantine, "Ratio and frontier analysis for assessing corporate performance: Evidence from the grocery industry in the UK," Journal of the Operational Research Society 46: 427-440, 1995.
[14] G. Gregoriou, J. Messier and K. Sedzro "Assessing the relative efficiency of Credit Union Branches Using Data Envelopment Analysis," INFOR 42: 281-297, 2005.
[15] H. Sherman and F. Gold, "Bank branch operating efficiency: evaluation with data envelopment analysis," Journal of Banking and Finance 9: 297-315. 1985.
[16] B. Gutiérrez-nieto, C. Serrano-cinca and C. Mar Molinero C, "Social efficiency in microfinance institutions," The Journal of the Operational Research Society 60: 104-119, 2009.
[17] B. Gutiérrez-nieto, C. Serrano-cinca and C. Mar Molinero C, "Microfinance institutions and efficiency," OMEGA The International Journal of Management Science 35: 131-142, 2007.
[18] L. Simar and P. W. Wilson, "A general methodology for bootstrapping in non-parametric frontier models," Journal of Applied Statistics 27: 779-802. 2000a.
[19] L. Simar "Detecting outliers in frontier models: A simple approach," Journal of Productivity Analysis 20: 391–424, 2003.
[20] D. C. Wheelock and P. W. Wilson, "Non-parametric, unconditional quantile estimation for efficiency analysis with an application to Federal Reserve check processing operations," Journal of Econometrics 145: 209-225.
[21] Wheelock D C and Wilson P W (2009 «Robust nonparametric quantile estimation of efficiency and productivity change in U.S. commercial banking, 1985-2004. Journal of Business & Economic Statistics 27: 354-368.
[22] L. Simar and P. W. Wilson, "Statistical inference in nonparametric frontier models: The state of the art" Journal of Productivity Analysis 13: 49-78. 2000b.
[23] R. W. Shephard, *Theory of Cost and Production Functions*, Princeton University Press. 1970.
[24] R. Färe and S. Grosskopf, *New directions: efficiency and productivity*, Springer Verlag 2005.
[25] C. Cazals, J. P. Florens and L. Simar, "Nonparametric frontier estimation: A robust approach," Journal of Econometrics 106: 1-25, 2002.
[26] C. Daraio and L. Simar, "Introducing environmental variables in nonparametric frontier models: A probabilistic approach," Journal of Productivity Analysis 24: 93–121, 2005.
[27] P. W. Wilson, "FEAR 1.0: A software package for frontier efficiency analysis with R," Socio-Economic Planning Sciences 42: 247-254, 2008.
[28] D. Deprins, L. Simar and H. Tulkens, "Measuring labor inefficiency in post offices," In: Marchand M, Pestieau P, Tulkens H ed. The Performance of Public Enterprises: Concepts and Measurements. North-Holland, Amsterdam, pp. 243-267, 1984.
[29] M. J. Farrell, "The measurement of productive efficiency," Journal of the Royal Statistical Society 120: 253-281, 1957.
[30] A. Charnes, W. W. Cooper and E. Rhodes "Measuring the efficiency of decision making units," European Journal of Operational Research 2: 429-444, 1978.
[31] K. Sedzro, M. Keita and T. Assogbavi, "The Impact of the organizational structure on the performance of microfinance institutions using data envelopment analysis," In: Kenneth DL, Gary K (ed) Applications in multicriteria decision making, data envelopment analysis, and finance (Applications of Management Science, Volume 14, Emerald Group Publishing Limited. pp.293-308, 2010.
[32] M. Haq, M. Skully and S. Pathan, "Efficiency of Microfinance Institutions: A Data Envelopment Analysis," Asia-Pacific Financial Markets 17: 63-97, 2010.
[33] United Nations "National Accounts Main Aggregates Database" http://unstats.un.org.proxy.bibliotheques.uqam.ca:2048/unsd/snaama/dnl list.asp. Accessed 15 september 2011.
[34] M. Yunus "Creating a world without poverty: social business and the future of capitalism" PublicAffairs, 2009.
[35] M. Yunus "Building social business: The new kind of capitalism that serves humanity's most pressing needs. PublicAffairs, 2011.
[36] C. Kao and S. Liu, "Predicting bank performance with financial forecasts: A case of Taiwan commercial banks," Journal of Banking and Finance 28: 2353-2368, 2004.
[37] A. N. Berger and D. B. Humphrey, "Efficiency of financial institutions: International survey and directions for future research," European Journal of Operational research 98: 175-202, 1997.
[38] Q. J. Yeh, "The application of Data Envelopment Analysis in Conjunction with financial ratios for bank performance evaluation," Journal of Operational Research Society 47: 980-988, 1996.
[39] T. F. Siems and R. S. Barr, "Benchmarking the productive efficiency of U.S. banks," Financial industry Studies, Federal Reserve Bank of Dallas 98: 11-24, 1998.
[40] R. S. Barr, K. A. Killgo, T. F. Siems and S. Zimmel, "Evaluating the productive efficiency and performance of U.S. commercial banks," Managerial Finance 28: 3-25, 2002.
[41] S. Navajas, M. Schreiner, R. L. Meyer, C. Gonzalez-Vega, and J. Rodriguez-Meza, "Micro credit and the Poorest of the Poor: Theory and Evidence from Bolivia," World Development 28: 333-346, 2000.
[42] R. Cull, A. Demirgüç-Kunt and J. Morduch, "Financial performance and outreach: A global analysis of leading microbanks," Economic Journal 117: 107-133, 2007.
[43] A. González, "Defining responsible financial performance: understanding efficiency," Microbanking Bulletin (May 2011): 1-5
[44] J. F. Burgess and P. W. Wilson, "Variation in inefficiency among US hospitals," Canadian Journal of Operational Research and Information Processing, INFOR 36: 84-102, 1998.
[45] K. R. Stanton, "Trends in relationship lending and factors affecting relationship lending efficiency," Journal of Banking and Finance 26: 127-152, 2002.

[46] C. P. Barros, "Measuring performance in defence-sector companies in a small NATO member country," Journal of Economic Studies 31: 112-128, 2004.

[47] C. C. Okeahalam, "Foreign ownership, performance and efficiency in the banking sector in Uganda and Botswana," Journal for Studies in Economics and Econometrics 28: 89-118, 2004.

[48] A. Alfonso and M. S. Aubyn, "Cross-country efficiency of secondary education provision: A semi-parametric analysis with non-discretionary inputs," Economic Modelling 23: 476-91, 2006.

[49] C. P. Barros and A. Assaf, "Bootstrapped efficiency measures of oil blocks in Angola" Energy Policy 37: 4098-4103, 2009.

[50] C. P. Barros and P. Garcia-del-Barrio, "Productivity drivers and market dynamics in the Spanish first division football league," Journal of Productivity Analysis 35: 5-13, 2011.

[51] L. Simar and P. W. Wilson, "Estimation and inference in two-stage, semi-parametric models of productions processes," Journal of Econometrics 136: 31-64, 2007.

[52] D. Hulme and P. Mosley, *Finance Against Poverty*, Volumes 1 and 2, Routledge, London, 1996.

[53] G. Woller and W. Woodworth, "Microcredit: a Grassroots Policy for International Development," Policy Studies Journal 29: 267-282, 2001.

[54] B. Haley, and J. Morduch, "Microfinance et réduction de la pauvreté : quel est le résultat? " In : Guerin I and Servet J M. Exclusion et Liens Financiers-Rapport du Centre Walras 2003, Paris : Economica, 2004. pp 549-560.