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DEA and SFA Research on the Efficiency of Microfinance Institutions: a Meta-Analysis

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Abstract:

Microfinance has played a key role in the fight against exclusion and the promotion of entrepreneurship in developing countries. An important question today is how to increase the reach and profitability of microfinance, in a context where subsidies are withdrawing to promote the viability and sustainability of microfinance institutions (MFIs). Efficiency analysis has found favor in this context and has attracted growing interest among professionals, partners, and researchers. Abundant empirical work has been conducted over the last ten years on this subject, in very different contexts and with different methodologies. The purpose of this article is to provide a meta-regression analysis on parametric and nonparametric estimations of Mean Technical Efficiency (MTE) in microfinance, using a data set of 262 observations from 38 studies. The results show that, in the microfinance industry, MTE scores have increased over time. However, with an MTE rate of approximately 61.1%,

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there is room for improving efficiency. MFIs use more resources than necessary for the results achieved in terms of outreach and revenue generated. Our results show heterogeneity of MTE according to the methodological approach of the studies. Studies with a larger number of variables (inputs and outputs) produced higher MTE scores than did those with a smaller number of variables. Studies using the variable returns to scale assumption resulted in higher MTE scores than those using constant returns to scale. In addition, those with a production approach had higher MTEs than did those using the intermediation approach, while studies of a large number of MFIs had lower scores than did those involving a small sample size. Moreover, research estimating social efficiency generated lower MTEs compared to those estimating financial efficiency. Studies using data from African MFIs obtained lower MTEs than did those on MFIs in Latin America and MENA, which confirms the poor performance of African microfinance.

1. INTRODUCTION

Microfinance has played a key role in the fight against exclusion and the promotion of entrepreneurship in developing countries (Dupas and Robinson, 2013; Khandker 2001; Pitt and Khandker, 1996). Microfinance differs from classical banking in particular because of its dual social and commercial mission, which also creates constant pressure for the microfinance institutions (MFIs) that truly pursue this double objective. Today, additional pressure has been added: the gradual withdrawal of subsidies for microfinance. Increasingly, donors are withdrawing from the microfinance sector because they are concerned about the continued existence of MFIs. Therefore, the overarching goal of microfinance institutions has become demonstrating viability. At the same time, management practices in MFIs have prioritized efficiency and cost reduction (Blanco-Oliver et al., 2016). This particular context has created an interest in research on the effectiveness of microfinance, making it a crucial issue today. This body of research provides empirical evidence on the sources of waste and inefficiencies in microfinance, key information for regulatory authorities and MFI managers. Also, with increasing financing by the capital market, efficiency analysis is a growing priority in this industry. Moreover, this interest in microfinance efficiency can be explained by greater

awareness of the role of efficiency in reconciling the social and financial objectives of microfinance (see Ben Soltane, 2008). For these reasons, over the past ten years there has been an abundance of empirical research analyzing microfinance efficiency.

Studies on microfinance efficiency have essentially adopted two main estimation methodologies: Data Envelopment Analysis (DEA), a nonparametric approach to data envelopment, and Stochastic Frontier Analysis (SFA), a parametric approach to estimation by stochastic boundaries. Empirical research on this issue has also been conducted in different regions, with different data, and for different periods. Studies have also covered very different MFIs in terms of their status, size, primary orientation, etc. Although the results seem to converge towards the low efficiency of microfinance, the studies have yielded rather disparate results. Despite the abundance of research, the literature has not yet provided empirical evidence about the factors that influence efficiency estimates. Another difficulty is that the techniques often used (DEA and SFA) are debatable because of their inherent weaknesses. Therefore, if we want an accurate appreciation of the role estimation techniques play and of the characteristics of studies on Mean Technical Efficiency (MTE) in microfinance, an overall analysis of current research is necessary. To date, such a study is non-existent in microfinance.

The purpose of this article is therefore to provide a meta-regression analysis on parametric and nonparametric estimations of MTE in microfinance. The challenge is to see how the methods used and the characteristics of these studies influenced their estimation of MTE. We focus particularly on the following questions: Can the differences in MTE results be explained by differences in methods? Is the MTE score determined by study characteristics such as sample size, study area, number of variables, date of publication, or quality of the journal in which it is published? Is the MTE score influenced by the returns to scale specification used (CRS *vs.* VRS)? Do the results change depending on whether the estimated model examines

social or financial efficiency? Does the MTE score change when moving from an intra-country to an inter-country level?

These major issues have not been addressed in the microfinance literature. In fact, the literature does not provide a clear indication of the extent to which the efficiency estimates are sensitive to the methodological choices used and the characteristics of each study. The present article aims to fill this gap through a meta-analysis, a technique that explains the variations in the empirical results of a given indicator on the basis of the characteristics that differentiate the studies. We used a doubly-censored Tobit model with cluster option that provides robust estimates when the dependent variable is bounded between 0 and 1. In order to gauge model robustness, we also estimated an OLS model with the cluster option, which is commonly used in this type of analysis, as well as a simple left- and right-censored Tobit model (see Thiam et al., 2011; Bravo-Ureta et al., 2007). Given the risk of correlations between the estimated technical efficiency scores and the study characteristics, we also used a Simar and Wilson model (2007) with the bootstrap option. These models compare MTE scores with the characteristics of each study, such as estimation method, number of variables, sample size, different choices of specifications, the region where the MFIs are located, etc.

The results show that in the microfinance industry, MTE scores have increased over time. However, with an MTE rate of approximately 60%, there is room for improving efficiency by 40%. The discrepancies between studies in their estimations of technical efficiency depended on the number of variables used, the specification choices, the number of MFIs studied, the region the MFI was located in, and the scale of analysis. Studies with a larger number of variables (inputs and outputs) produced higher MTE scores than those with a smaller number of variables. Studies using the variable returns to scale (VRS) assumption resulted in higher MTE scores than those using constant returns to scale (CRS). In addition, those with a production approach had higher MTEs than those using the intermediation approach, while

studies of a large number of MFIs had lower scores than those involving a small sample size. Moreover, research estimating social efficiency generated lower MTEs compared to those estimating financial efficiency. Studies using data from African MFIs obtained lower MTEs than those on MFIs in Latin America and MENA.

This article thus makes an important contribution to the literature as it is the first meta-analysis on microfinance efficiency, to our knowledge. The results provide major insight into the factors of inter-study variabilities in estimating efficiency in this industry. The article is organized as follows: first, we briefly review the conceptual framework of efficiency and the main estimation methods in microfinance (section 2); then we present the methodology and the study data (section 3), as well as the results obtained (section 4); finally, we conclude (Section 5).

2. THE CONCEPT OF TECHNICAL EFFICIENCY AND THE FRONTIER METHODOLOGY IN MICROFINANCE

Technical efficiency (TE) in microfinance refers to the efficiency with which MFIs use resources in the production process (Widiarto and Emrouznejad, 2015). It expresses the capacity of decision-making units (DMUs, MFIs here) to produce the maximum number of outputs with a given quantity of inputs or, conversely, to mobilize the minimum inputs for a given level of outputs. When an MFI is unable to proportionally increase its output without also increasing its inputs, it is said to be technically efficient. However, technical efficiency (TE) is only one aspect of efficiency, as Farell (1957) emphasizes. Another component of efficiency is allocative efficiency. In microfinance, this refers to the efficient combination of inputs and outputs that takes into account input prices and their productivity. In this perspective, an MFI is said to be efficient if it manages to minimize its production costs or to maximize its revenues. The economic efficiency of a decision-making unit (MFI) is thus the

sum of technical efficiency and allocative efficiency. This article focuses on technical efficiency, not only because it is the most studied in the literature, but it is also easier to estimate. Calculating allocative efficiency, in fact, requires information on the prices of inputs and outputs, which is very difficult to obtain in microfinance.[2]

Among all the techniques for estimating efficiency in general and microfinance in particular, there are two main approaches: parametric and nonparametric. The former is based on an econometric estimate of the efficiency frontier and subdivides into two groups: deterministic parametric approaches and stochastic ones. The specificity of deterministic methods is that they consider any deviation from the frontier as a result of inefficiency. Thus, they risk being biased, especially when the data are affected by measurement errors. As an alternative, there are stochastic frontier methods, of which SFA is the best-known. Compared to conventional parametric methods such as OLS, the SFA approach is distinctive because the error term breaks down into a two-sided component: a normally distributed random error term (μ) that takes into account exogenous factors beyond the firm's control, and an error term (υ) representing the firm's technical inefficiency. First introduced by Aigner, Lovell and Schmidt (1977), this approach has been widely used in assessing banking efficiency and more recently in microfinance. Its main advantage lies in separating the inefficiency that results from random shocks from that which results from the technical inefficiency of the firm. This breakdown explains why SFA generally gives lower MTE results than DEA. In addition, SFA models can be used to estimate errors and test hypotheses (Odeck and Brathen, 2012).

However, parametric approaches, whether deterministic or stochastic, must specify the functional form of the production or cost function that serves as the basis for estimating the

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[2] This is often the case in other areas such as banking, education, healthcare, agriculture, etc. but is even more pronounced in microfinance.

efficiency frontier. Some empirical studies have used the SFA approach for estimating microfinance efficiency (Hermes et al. 2009; Oteng-Abayie et al., 2011; Masood and Ahmad, 2010; Servin et al., 2012; Desrochers and Lamberte, 2003; Quayes and Khalyli, 2014; Riaz and Gopal, 2015; Bos and Millone, 2015; Mor, 2016). Among them, some have estimated a cost function (Riaz and Gopal, 2015; Billi and Thi, 2012), while others a production function (Bos and Millone, 2015; Hermes et al., 2011). The disadvantage of SFA in microfinance lies in the difficulty of specifying a typical production function, as there are many different situations in microfinance.

In contrast, nonparametric approaches require no specification of the functional form. They are based on the mathematical estimation of a linear programming function that connects inputs and outputs. Two main approaches stand out in this group: the DEA model and the FDH (Free Disposal Hull) model. In microfinance research, DEA is predominant.[3] This method consists in the nonparametric estimation of an efficiency frontier that envelops the ensemble of individuals and makes it possible to identify best practices, those located on the frontier. It was initially developed by Charmes, Cooper and Rhodes (1978) and Banker (1984), based on the theoretical framework of Farell (1957). Unlike SFA, DEA is a deterministic method that also has many advantages. Beyond the fact that it does not require any specification of the functional form of the frontier, it is flexible and well-suited to multi-product industries such as microfinance. Its fundamental limitation is its high sensitivity to data, sample size, and measurement errors. In these cases, DEA leads to biased estimates (Greene, 1993).

There is a great deal of efficiency research in the banking industry (see Berger and Humphrey, 1997; Battese, G., Coelli, T., 1995; Battese et al., 2004; Berg et al., 1995 ; Berger

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[3] To date, we have not identified any studies that use HDF to estimate microfinance efficiency.

et al., 1993; Bos et Kool, 2001 ; Bos et Schmiedel, 2003). In microfinance, such work is more recent and integrates new aspects. For example, the dual objective of microfinance calls for additional considerations when analyzing efficiency. In particular, taking into account social efficiency, in addition to financial efficiency, is essential. Although this was not often done in previous research (Nghiem et al., 2006, Qayyum and Ahmad, 2006, Gutiérrez-Nieto et al., 2007, Ben Soltane 2008, Hassan and Sanchez, 2009), the social aspect has been increasingly integrated in recent studies (Akram and Ahmad, 2016, Cornée and Tenet, 2016, Van Damme et al., 2016, Basharat et al., 2015, Lebovics et al., 2016, Widiarto and Emounznejad, 2015, Wijesiri, Viganò and Meoli, 2015). Moreover, in estimating efficiency, as financial intermediaries MFIs have been judged by the yardstick of banking theory. In this theory, there are two main approaches: production and intermediate (Sealey and Lindley, 1977; Berger and Humprey, 1997). In microfinance, most studies have focused on production (Wijesiri, Viganò and Meoli, 2015 ; Ben Soltane, 2008; Gutiérrez-Nieto et al., 2007; Haq et al., 2010; Nghiem et al., 2006), in particular because not all MFIs are allowed to collect savings from the general public. Nevertheless, some studies have chosen an intermediation approach (Wijesiri, Viganò and Meoli, 2015, Ben Soltane, 2008, Gutiérrez-Nieto et al., 2007, Haq et al., 2010, Nghiem et al. 2006). Some have also combined the two approaches (Piot-Lepetit and Ngongang, 2014). In addition, research breaks down into an input orientation or an output one. Both types of orientation generally provide the same results. Finally, the assumption underlying the estimate is also determinant: most microfinance models have been estimated using variable returns to scale (VRS) due to the low maturity of this industry, but also because of different regulations depending on the contexts and status of microfinance. VRS models also result in higher efficiency scores than the CRS ones, which this study will verify.

3. DATA AND METHODOLOGY

a. Data

This meta-analysis includes all research analyzing microfinance efficiency between 2006[4] and 2016. The studies selected were mainly published in peer-reviewed journals but some working papers have been included (Hassan and Sanchez, 2009, Ahmad, 2011, Abdelkader et al., 2012, Kablan, 2012). The latter are major works on microfinance efficiency and are very often cited in the literature, including studies published in the best journals. The integration of unpublished works is also well-viewed in meta-analysis, in particular to avoid selection bias. The studies examined were identified through platforms such as Sciencedirect, Mendeley, Springer, Jstor, SSRN, Google Scholar, etc. Some well-known studies on efficiency were excluded here because the technical efficiency score was not indicated and the information provided did not enable us to calculate it. This was the case for example with studies by Servin et al. (2012), Hartarska et al. (2013), Ben Soltane (2014), Wijisiri and Moeli (2015), and Mia and Ben Soltane (2016). We also excluded studies using the malmquist DEA to estimate microfinance productivity, since this research relates to productivity and not technical efficiency.

In the end, this study includes 38 articles that used DEA or SFA to estimate the efficiency of microfinance. For each study selected, we collected data on the MTE and study characteristics such as estimation choices, sample size, number of variables, year of data used, region, etc., following research on meta-analysis (Thiam et al., 2001 ; Bravo-Ureta et al., 2007 ; Moreira-Lopez and Bravo-Ureta, 2009 ; Odeck and Brothen, 2012 ; Ogundari, 2014 ; Fatimata and Yasmin, 2016). Table 1 gives the studies' characteristics.

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[4] The first study on this subject in microfinance dates from 2006.

Table 1: Characteristics of the studies reviewed

Study	Author(s)	Publication year	Data Type	Year of data	Basic model	Number of observations	MTE score
I. Nonparametric DEA frontiers							
1	Qayyum and Ahmad (2006)	2006	Cross-sectional	2006	DEA	15	39.5
2	Gutiérrez-Nieto et al. (2007)	2007	Cross-sectional	2003	DEA	30	32.7
3	Gutiérrez-Nieto et al. (2009)	2009	Cross-sectional	2003	DEA	89	35.53
4	Ben Soltane (2008)	2008	Cross-sectional	2004	DEA	35	64.44
5	Singh et al. (2013)	2013	Cross-sectional	2009	DEA	41	40.6
6	Ahmad (2011)	2011	Cross-sectional	2003	DEA	12	54.8
7	Singh (2014)	2014	Panel	2013-2014	DEA	30	63.56
8	Haq et al. (2010)	2010	Cross-sectional	2004	DEA	39	38.3
9	Cornée and Tenet (2016)	2016	Cross-sectional	2006	DEA	61	90.92
10	Wijesiri et al. (2015)	2015	Cross-sectional	2010	DEA	36	39.67

11	Piot-Lepetit and Nzongang (2014)	2014	Cross-sectional	2009	DEA	52	87.5
12	Widiarto and Emounznejad (2015)	2015	Cross-sectional	2009	DEA	204	78.24
13	Gueyie et al. (2010)	2010	Cross-sectional	2006	DEA	20	93.7
14	Tahir and Tahrim (2013)	2013	Cross-sectional	2008	DEA	140	69.97
15	Kipesha (2012)	2012	Cross-sectional	2009	DEA	35	70.6
16	Jayamaha (2012)	2012	Cross-sectional	2005	DEA	125	73.6
17	Segun and Anjuvan (2013)	2013	Panel	2008 à 2010	DEA	70	23.2
18	Abdelkader et al. (2012)	2012	Cross-sectional	2006	DEA	40	83
19	Annim (2010)	2010	Cross-sectional	2004	DEA	164	42.7
20	Nzongang et al. (2012)	2012	Cross-sectional	2009	DEA	52	78.45
21	Kablan (2012)	2012	Cross-sectional	2000	DEA	104	43.07
22	Hassan and	2009	Cross-	2005	DEA	141	70

	Sanchez (2009)		sectional			
23	Van Damme et al. (2016)	2016	Cross-sectional	2011	DEA	36	75.27
24	Lebovics et al. (2015)	2015	Cross-sectional	2011	DEA	28	94.5
25	Akram et al. (2016)	2017	Cross-sectional	2008	DEA	170	86.7
26	Basharat et al. (2015)	2015	Panel	2005-2008	DEA	57	82.57
27	Ferdousi (2013)	2013	Cross-sectional	2010	DEA	42	40.3
28	Tahir and Tahrim (2015)	2015	Cross-sectional	2008	DEA	13	91.1
29	Nghiem et al. (2006)	2006	Cross-sectional	2006	model	44	76

II. Parametric stochastic frontiers

1	Oteng-Abayie et al. (2011)	2011	Panel	2007-2010	SFA	135	56.29
2	Masood and Ahmad (2010)	2010	Panel	2005-2008	SFA	40	34.01
3	Servin et al.(2012)	2012	Panel	2003-2009	SFA	1681	58.1
4	Desrochers and Lamberte (2003)	2003	Panel	1995 -1999	SFA	50	0.4
5	Quayes and	2014	Cross-sectional	2004	SFA	45	2.22

	Khalyli (2014)		sectional				
6	Hermes et al. (2009)	2009	Panel	1997 - 2007	SFA	435	46.92
7	Riaz and Gopal (2015)	2015	Panel	2007 - 2013	SFA	148	87
8	Bos and Millone (2015)	2015	Panel	2003 - 2010	SFA	3880	28.23
9	Mor et al.	2016	Cross-sectional	2014	SFA	78	64.03

Source: authors

Tables 2 and 3 below give some descriptive statistics on the studies analyzed. Table 2 clearly shows that nonparametric approaches dominate the literature. Of the 38 studies included in this meta-analysis, 29 used the DEA approach compared with only 9 for SFA. Since some articles, including DEA studies, estimated several models, the 35 studies produced a total of 262 MTEs, of which 230 are DEA and 32 are SFA. These models were estimated in several different contexts: Asia, Latin America, MENA (Middle East and North Africa) and Africa. Work was mainly conducted in Asia (38.7%) and in MENA (43.7%), with much less work on Africa (3.6%).

Table 2: Quantitative survey of the literature

	Nonparametric studies (DEA)	Parametric studies (SFA)	Total sample
All			

Number of studies	29	09	38
Number of data points	230	32	262
Mean TE	0.629	0.484	0.611
Data			
Cross-sectional	79.8%	6.5%	86.3%
Panel	8.0%	5.7%	13.7%
TE-orientation			
Input saving	77.9%	7.3%	85.1%
Output increasing	9.9%	5.0%	14.9%
Nonparametric specification			
CRS	47.8%		
VRS	52.2%		
Region of study			
Africa	24.4%	0.4%	24.8%
Asia	32.8%	3.1%	35.9%
Latin America	12.6%	2.7%	15.3%
MENA	5.3%	12.6%	17.9%
World	12.6%	6.1%	18.7%
Scale of Analysis			
Intra country	35.5%	52.3%	87.8%
Inter country	52.3%	8.0%	60.3%
Finance vs social			
Finance	11.8%	0.8%	12.6%
Mixed	66.8%	11.1%	77.9%

Social	9.2%	0.4%	9.5%

We note that the MTE estimated by these studies is approximately 60% for the microfinance industry. This result points to the inefficiency of this industry in the technical management of resources and shows that the potential for improving efficiency in this industry is approximately 40%. Concerning the type of data used, most studies worked with cross-sectional data (86.9%), compared with only 15.3% for panel data. Most studies chose input orientation (84.7%) and very few chose output (15.3%). In the DEA studies, 57.4% of the estimated models used the VRS assumption and 42.6%, CRS. As noted above, this choice is generally justified by the imperfect competition in this industry and the fact that a large majority of MFIs have not yet matured. Most of the work estimated a mixed model of financial efficiency (77.9%) while very few estimated a social efficiency model (9.5).

Table 3: MTE scores by different study characteristics

	Nonparametric studies (DEA)	Parametric studies (SFA)	Total sample
All	0.629	0.484	0.611
Data			
Cross-sectional	0.622	0.388	0.605
Panel	0.692	0.592	0.650

TE-orientation			
Input saving	0.646	0.484	0.633
Output increasing	0.490	0.483	0.488
Nonparametric specification			
CRS	0.561	0.000	0.000
VRS	0.691	0.000	0.000
Region of study			
Africa	0.630	0.563	0.629
Asia	0.649	0.331	0.622
Latin America	0.614	0.660	0.622
MENA	0.733	0.000	0.733
World	0.544	0.478	0.522
Scale of Analysis			
Intra country	0.655	0.345	0.622
Inter country	0.611	0.556	0.604
Finance vs social			
Finance	0.697	0.541	0.688
Mixed	0.626	0.474	0.604
Social	0.561	0.649	0.565

Source: authors

Table 3 details the MTE estimated. TE was higher in the VRS models (68.42%) than in the

CRS models (48.98%). The MTE score was lower in SFA models (42.37% versus 62.45% in

DEA models). The MTE scores in Africa (77.54%) and Asia (64.87%) were above the global

average, while in Latin America and the MENA region it was slightly below average. Finally, MTE was lower in studies examining social efficiency (56.5%) as compared to financial efficiency (68.8) and the mixed models (60.4).

b. Methodology

We hypothesize that the different microfinance MTE levels would be explained by factors specific to each study, such as the estimation methodology (DEA, SFA), the sample size, the number of inputs and outputs in the model, choice of basic assumptions in estimation, microfinance context, etc. In order to test these hypotheses, we estimate the following empirical model:

$$MTE_i = X_i\beta + E_i \qquad (1)$$

MTE_i is the mean technical efficiency score estimated by study i; X_i is the vector of the characteristics of study i which are supposed to explain its MTE. Model errors are given by E. Given the censored nature of the dependent variable, the equation can be rewritten as a Tobit model (Greene, 1997):

$$MTE_i = \begin{cases} TE_i & if \ 0 \leq TE_i \leq 1 \\ 0 & if TE_i < 0 \ ou \ TE_i > 1 \end{cases} \qquad (2)$$

Equation (1) then becomes:

$$MTE_i = \beta_0 + \beta_1 AV_{DATA_{Y_i}} + MODEL_i + N_{VAR_i} + OPTION_i + EFF\_TYPE\_SOC_i$$
$$+ EFF\_TYPE\_MIX_i + APPROACH_i + SIZE_i + STUD\_TYPE_i + DATA\_TYPE_i + RANG_i + REGION$$

$$(3)$$

With *MTE* as the mean technical efficiency found in each study; *AV_DATA_Y* is the mean year of the study data; *MODEL* is a categorical variable with two options that indicates the model used for estimating MTE (DEA or SFA); *N_VAR* is the number of variables (inputs and

outputs) in the model; *OPTION* is a categorical variable that takes either the CRS or VRS assumption; *EFF_TYPE_Soc* is a categorical variable that was scored SOCIAL when the study estimated a social model and FINANCIAL when the study estimated a financial model; *EFF_TYPE_MIX* is a categorical variable that is *Mixed* when the study estimated a mixed model and *Financial* when the study estimated a financial model; *APPROACH* is a categorical variable with PRODUCTION when the study was estimated with the production approach and INTERMEDIATION when used the intermediation approach; *SIZE* represents the sample size of the study, i.e. the number of MFIs studied; *STUD_TYPE* is a categorical variable that takes the INTRA modality if the study was carried out within the same country and CROSS when it covered several countries; *DATA_TYPE* is a variable that designates the type of data used; it with either PANEL when it is panel data or CT for cross-sectional data; RANG is a dummy variable with a value 1 when the study is published in a rank 1 academic journal and 0 otherwise; *REGION* is a variable that designates the study region with five options (Africa, Asia, Latin America, Mena, World), with Africa as the reference. It breaks down in several ways depending on the regions compared directly. Due to the very limited number of SFA studies, we chose not to introduce a variable to distinguish the Cobb Douglas and Translog functions. We estimated a left- and right-censored Tobit model since the efficiency scores range from 0 to 100. We estimated the same model with the cluster option to account for heteroscedasticity problems that might arise from data belonging to the same study. We termed this model the 'clustered Tobit model'. We also estimated an OLS model and a truncated bootstrap model from Simar and Wilson (2007) to gauge the robustness of our results. Estimating Simar and Wilson's model (2007) is justified by the potential correlation between the endogenous variable and the characteristics of each study. This method also enabled us to determine the data generating process of our sample, which is not the case with the other models. We used algorithm 1 from Simar and Wilson (2007), which is more suitable

for samples of relatively large size. For more details on this algorithm, see Simar and Wilson (2007).

4. RESULTS AND DISCUSSION

Table 4 below gives the results of the four estimated models: OLS, Tobit, clustered Tobit, and truncated bootstrap by Simar and Wilson (2007). Overall, the results of the four are similar. The estimated parameter for the mean year of the data (AV_DATA_Y) was positive and statistically significant, showing that MTE has increased over time in the microfinance industry. Intuitively, this result may indicate that the microfinance industry has gradually increased its efficiency in resource management. This result is consistent with Thiam et al. (2001). The latter conducted a meta-analysis in agriculture and found a positive relationship between MTE and the year of publication of the study[5]. Ogundari and Brümmer (2011) also found a significant increase in MTE over time. Odeck and Brothen (2012), in a meta-analysis on the efficiency of seaports, instead found a negative relationship. Brons et al. (2005) also found that more recent studies estimated a lower efficiency score than previous studies.

MTE increased significantly with the number of variables in the model. The estimated coefficient of the variable N_VAR was positive and significant in all the models here (at the 1% threshold). Thus studies that estimated technical efficiency with a greater number of variables obtained higher average scores. This is a standard result that highlights the sensitivity of the DEA method regarding the number of integrated variables. This result is consistent with Nguyen and Coelli (2009), which found a positive impact of the number of variables on MTE. Gutiérrez-Nieto et al. (2007) described several models based on different

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[5] However, our study uses the average data year as the proxy for the date, which is not the case for Thiam et al. (2001).

combinations of input and output, and their results clearly indicate higher technical efficiency scores in models with more inputs and outputs.

The results also show that studies with the variable returns to scale assumption generated a higher MTE score than those with constant returns to scale. This is also a standard result in efficiency estimation. Since the VRS assumption is less restrictive than CRS, the estimated mean efficiency is generally higher. The same result was obtained by Odeck and Brothen (2012) and Nguyen and Coelli (2009).

The sample size variable (SIZE) had a negative coefficient and was very significant in all models (threshold of 1%), showing that the MTE is lower in large-sample studies than in small-sample studies. This result is common in meta-studies on efficiency (Nguyen and Coelli, 2009, Aiello and Bonanno, 2015).

The coefficient of the type of efficiency variable (EFF_TYPE_Social) was negative and significant in all models; thus studies estimating a social efficiency model yielded lower efficiency scores than those on financial efficiency. This may be explained by the fact that social efficiency is more constraining for MFIs than financial efficiency.

The data also show that studies adopting a production approach generated a higher mean efficiency score than those with an intermediate approach. Similarly, work in the MENA and Latin America regions estimated higher efficiency scores than those in Africa. The STUD_TYPE, RANG, and REGION_WORLD variables were not significant in the OLS, Tobit, and Clustered Tobit models, but were significant in the more robust truncated bootstrap Simar and Wilson model. In addition, studies within the same country yielded higher mean efficiency scores than those carried out in several countries. Studies published in rank 1 journals estimated higher MTE scores than those published in lower ranking journals.

Moreover, the results also show that studies at the global level generated higher efficiency scores than those in Africa. The DATA_TYPE, MODEL variables often studied in meta-analyses were not significant in all estimated models. However, their signs are intuitive. The coefficient of the variable (DATA_TYPE) was positive, showing that studies using panel data had a higher mean efficiency score than those using cross-sectional data. The negative coefficient of the DATA_TYPE variable revealed higher scores in studies using panel data. This result is in line with Aiello and Bonanno (2016), but in contrast to Odeck and Brothen (2012). However, this result is not statistically significant. Finally, studies that estimated an SFA model produced a lower MTE score than those with a DEA model. This is a traditional but unfortunately not statistically significant result.

Table 4: Regression Results

	OLS	Tobit	Clustered tobit	Simar & Wilson
main				
AV_DATA_Y	2.380***	2.380***	2.380***	3.105***
	(0.830)	(0.443)	(0.805)	(0.555)
Model: SFA	-3.541	-3.541	-3.541	-6.032
	(10.737)	(4.891)	(10.424)	(5.929)
N_VAR	5.526***	5.526***	5.526***	7.981***
	(1.688)	(0.765)	(1.639)	(1.088)
OPTION	10.72***	10.72***	10.72***	13.733***
	(2.731)	(2.488)	(2.651)	(3.149)
EFF_TYPE:Mixed	1.637	1.637	1.637	4.588

	(6.496)	(4.202)	(6.306)	(5.47)
EFF_TYPE:Social	-13.14*	-13.14***	-13.14*	-16.451***
	(6.964)	(4.569)	(6.760)	(5.79)
APPROACH:Productio n	13.20*	13.20***	13.20*	14.564***
	(7.410)	(3.962)	(7.194)	(4.593)
SIZE	-0.0107***	-0.0107**	-0.0107***	-0.014***
	(0.003)	(0.004)	(0.003)	(0.005)
STUD_TYPE:Intra country	4.536	4.536	4.536	9.008**
	(5.834)	(3.015)	(5.664)	(3.646)
DATA_TYPE:Panel	5.110	5.110	5.110	7.654
	(7.644)	(4.139)	(7.420)	(5.134)
RANG_dummy==1	2.712	2.712	2.712	9.32**
	(6.154)	(3.365)	(5.974)	(4.231)
REGION:Asia	2.302	2.302	2.302	1.723
	(6.408)	(3.019)	(6.221)	(3.594)
REGION: Latin Am	17.78**	17.78***	17.78**	20.383***
	(7.989)	(4.422)	(7.755)	(5.639)
REGION:MENA	14.56**	14.56***	14.56***	18.754***
	(5.515)	(5.223)	(5.353)	(6.903)
REGION:World	7.738	7.738	7.738	12.85**
	(7.941)	(4.837)	(7.709)	(5.95)
_cons	-4765.6***	-4765.6***	-4765.6***	-6238.329***
	(1671.352)	(890.884)	(1622.503)	(1116.637)

sigma			
_cons		17.16***	17.16***	18.7***
		(0.750)	(1.384)	(0.987)
Observations	262	262	262	262
AIC	2265.0	2267.0	2267.0	
BIC	2322.1	2327.7	2327.7	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5. CONCLUSION

This study is the first to propose a meta-analysis of research on technical efficiency in microfinance. We estimated several models: a doubly-censored Tobit model, a clustered Tobit model, an OLS model, and a truncated bootstrap model from Simar and Wilson (2007). This research collected data from 38 studies estimating microfinance efficiency from 2006 to 2016. As some studies estimated several efficiency models, in the end we had 262 MTE results on which we performed the meta-analysis. The four estimated models provided similar results, highlighting the robustness of our findings. The results show an improvement in the level of microfinance efficiency over time, demonstrating better resource management in this industry. However, the level of efficiency of the industry as a whole remains weak and should be improved. With a 60% MTE, there is still great potential for improving efficiency in this industry.

The results show that the specifications as well as the characteristics of each study played a decisive role in estimated MTE scores. The score was higher in studies using a large

number of variables (inputs and outputs), those with a production approach, and those using the variable returns to scale (VRS) assumption. Studies of MFIs in Latin America and the MENA region also obtained a higher MTE score than those conducted on African MFIs. On the other hand, the MTE score was lower in studies with large sample sizes and those estimating a social model. The lesson we draw from this meta-analysis is that the divergences between studies on microfinance MTE relate to the differences between study characteristics and the choice of specifications.

The main limitation of the present study is that the analysis of microfinance efficiency is still recent and the number of studies carried out is still low. In particular, little work has been done with the SFA approach; DEA is more common in estimating microfinance efficiency. Yet the latter suffers from inherent weaknesses: it is highly sensitive to data and sample size and may lead to biased estimates if there are measurement errors or outliers. Robust approaches exist today, but have hardly been used in research on the microfinance industry. A diversification of estimation methodologies, including new robust approaches (order-alpha, order-m, etc.), would introduce more heterogeneity into the data used for meta-analysis. Despite this limit, the present study sheds considerable light on the factors of variability in estimating efficiency in the microfinance industry to date.

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