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The performance of microfinance institutions: An analysis of the local and legal constraints

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Global financial inclusion recently has been the focus of many international development agencies. Myriad of initiatives have been taken, amongst which microfinance has proved an unprecedent success in poverty alleviation, women empowerment and even macroeconomic growth through facilitation entrepreneurship for the underprivileged. Despite a promising outcome in global scale, not all Microfinance Institutions (MFIs) have witnessed a similar success. While in Asia subsidies and donations have been the key of MFIs survival, in Latin America commercialisation has brought success. In Asia microfinance gained the fame for high social outreach, and in Latin America for the subsidies-independency and financial sustainability. Much as it seems that location plays the main role, overtime the globalisation of microfinance and the expansion of standout MFIs led the role of geography to weaken. Now, global microfinance consists of many MFIs, such as FINCA, Grameen and Kiva that run in different countries, yet applying united strategies. Strong dynamism is also seen in the legal status of MFIs in such a way that many NGOs have been turning into Non-Bank Financial Institutions or non-deposit taking MFIs start to take deposit and form a bank status. In light of the fast pace dynamics in location and legal status of MFIs, we aim to shed light on the assessment of MFIs performance in achieving their dual objective. To do so, we analyse the performance of 462 MFIs regarding and regardless of their location and type heterogeneity so that they are compared to their peers inside and outside of typological and geographical constraints. The analysis provide insight about the share of inefficiency caused by the aforementioned constraints (called technology gap) and that of mismanagement and can be used by practitioners and policymakers to better decide on change in location and legal status of MFIs.

Keywords Microfinance, Performance, Location and Legal status Heterogeneity, Meta-frontier DEA

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Abstract

Global financial inclusion recently has been the focus of many international development agencies. Myriad of initiatives have been taken, amongst which microfinance has proved an unprecedent success in poverty alleviation, women empowerment and even macroeconomic growth through facilitation entrepreneurship for the underprivileged. Despite a promising outcome in global scale, not all Microfinance Institutions (MFIs) have witnessed a similar success. While in Asia subsidies and donations have been the key of MFIs survival, in Latin America commercialisation has brought success. In Asia microfinance gained the fame for high social outreach, and in Latin America for the subsidies-independency and financial sustainability. Much as it seems that location plays the main role, overtime the globalisation of microfinance and the expansion of standout MFIs led the role of geography to weaken. Now, global microfinance consists of many MFIs, such as FINCA, Grameen and Kiva that run in different countries, yet applying united strategies. Strong dynamism is also seen in the legal status of MFIs in such a way that many NGOs have been turning into Non-Bank Financial Institutions or non-deposit taking MFIs start to take deposit and form a bank status. In light of the fast pace dynamics in location and legal status of MFIs, we aim to shed light on the assessment of MFIs performance in achieving their dual objective. To do so, we analyse the performance of 462 MFIs regarding and regardless of their location and type heterogeneity so that they are compared to their peers inside and outside of typological and geographical constraints. The analysis provide insight about the share of inefficiency caused by the aforementioned constraints (called technology gap) and that of mismanagement and can be used by practitioners and policymakers to better decide on change in location and legal status of MFIs.

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Introduction

Modern microfinance (MF) is a tailored channel to address complex social issues through collateral free loans and financial facilities (Morduch, 1999a). The industry dates back to the late 1970s, and took a surge in 2006 when its pioneer, Muhammad Yunus, won a noble prize. Its distinguished promotion by renowned development agencies such as the United Nations has led the idea to be expanded and replicated in developing and even developed world as an effective economic development tool (Mia & Chandran, 2016).

The industry is coming of age and ever since its emergence, there is an ever-growing search for optimizing MFIs performance. In the 1980s and 1990s, the continuing dependency on subsidies and evidence of unsatisfactory performance resulted in the development of a new microfinance premise of self-sustainability. Donors started to put forward that subsidization should only support newly established MFIs instead of keeping them constantly afloat (Morduch, 1999). They argued that cost control and efficiency would ultimately reduce the dependency of the industry on subsidies, which would allow MFIs to stay in business in the long run. Besides this evolution, MFIs were also confronted with greater competition and increased interest from the private sector (Rhyne & Otero, 2006). Consequently, the industry fosters management tools that prioritize efficiency and cost reduction (Griffin & Husted, 2015). With higher stress on efficiency comes numerous shifts in the industry. Many NGO MFIs have turned to Non-Bank Financial Institutions (NBFIs) or banks and re-structure the ownership (D'Espallier, Goedecke, Hudon, & Mersland, 2017; Servin, Lensink, & Van den Berg, 2012). The competition has also accelerate the internationalisation of microfinance and involvement of multi-national banks with the aim of efficiency growth (Ault & Spicer, 2009; Roy Mersland, Zamore, Ohene Djan, & Sommeno, 2019),

Hence, large number of studies investigated MFIs performance and its determinants through different approaches. Earlier studies simply measured financial and social performance thorough single variables or ratios, whereas overtime multi-variate and frontier methods have been added to the literature to improve the analysis (Fall, Akim, & Wassongma, 2018). Amongst frontier approaches, Data Envelopment Analysis (DEA) is, in particular suitable for MFIs since it can handle multiple variables and evaluate the performance of each MFI through a benchmark of the best practices (Gutiérrez-Nietoa, Serrano-Cincaa, & Molinero, 2007; Mahinda Wijesiri, Viganò, & Meoli, 2015). This method is widely applied by past studies such as Ben Soltan Bassem (2008); Gutierrez-Nieto, Serrano-Cinca, and Molinero (2007); Postelnicu and Hermes (2015); Mahinda Wijesiri and Meoli (2015).

Despite their contribution, the existing literature disregarded the heterogeneity of MFIs in the production technology which adds to the complexity of meeting double bottom line objectives. More precisely, MFIs with different characteristics face different production opportunities. Technically, they make choices from different sets of feasible input–output combinations. These so-called technology sets differ because of differences in available stocks of capital, economic infrastructure, resource endowments and any other characteristics of the environment in which production takes place (O'Donnell, Rao, & Battese, 2008).

The heterogeneities that are also discussed as "performance determinants" are widely discussed in performance studies. So, for the sake of brevity we refer the reader to the well-discussed systematic review by (Niels Hermes & Hudon, 2018). Previous studies dealt with this in different ways. One way is to limit their evaluation to a one group that is assumed to consists of only homogeneous MFIs. This was mainly one specific region or country, such as Ben Soltan Bassem (2008); Gutiérrez-Nietoa et al. (2007) that evaluated performance of MFIs in MENA and Latin America, respectively or MFIs with specific type (microbanks, NBFIs or Islamic bank only) (Awoyemi & Jabar, 2014; Hosen, Rahman, & Dutta, 2013; King'ori, Kioko, & Shikumo, 2017; Paul, Ebelechukwu, & Yakubu, 2015). The second way is to pool heterogeneous MFIs in evaluation first and separate them in the second stage using a regression analysis such as (Ben Soltan Bassem, 2008; Piot-Lepetit & Nzongang, 2014; Singh, Mahapatra, Mukherjee, & Bhar, 2014; Mahinda Wijesiri et al., 2015). The other approach is to separate the model for different MFIs as is evident in Haq, Skully, and Pathan (2010) who show that under the production approach NGOs are more efficient while bank-microfinance institutions are the best performers under the intermediation approach.

However, there is often considerable interest in measuring the performance of firms across groups (e.g., comparing efficiency levels in African MFIs with efficiency levels in Asian MFIs or that of NBFIs with NGOs). Unfortunately, such comparisons are only meaningful in the limiting special case where frontiers for different groups of firms are identical. By applying DEA-meta-frontier, this study breaks down the relative efficiency of MFIs across the globe and provide an insight about best practices, given the heterogeneity in not only location but also type. We overcome this gap by measuring efficiency relative to a common meta-frontier, defined as the boundary of an unrestricted technology set. We also define group frontiers to be the boundaries of restricted technology sets, where the restrictions derive from characteristics of the production environment, as discussed above.

. Therefore, the "relative efficiency", measured based on "homogeneity" assumption is in fact unrealistic and unreliable. More precisely,.

To the best of our knowledge, this is the first study that consider the heterogeneity in type and location in analysing the performance of MFIs. Mahinda Wijesiri, Yaron, and Meoli (2017) is the only similar study in microfinance realm that considered this heterogeneity to assess the impact of size and age on the performance of MFIs within six regions. However, different ownership types lead MFIs to use different technologies and heterogeneous production possibilities and consequently different efficiency levels (Servin et al., 2012). Nowadays, there are many MFIs applying the same business model and having similar ownership structure in multiple countries (Bos & Millone, 2015). For example, BRAC, Grameen and Kiva that run MFIs in multiple countries, while following a unified business model and having access to a more homogeneous production technology. The variety of ownership structure leads to different regulatory and supervisory mechanisms, different agency problems, different governance models as well as different levels of risk preferences (Servin et al., 2012; Tchakoute-Tchuigoua, 2010). For example, banks and non-bank financial institutions (NBFIs) are shareholder based and focus more on financial returns. Cooperatives and non-governmental organizations (NGOs), on the other hand, are non-regulated and more socially-oriented (M. Wijesiri, 2016). Unlike non-regulated ownership types, banks and NBFIs are regulated and hence have more opportunities to offer a wider range of products and services (Tchakoute-Tchuigoua, 2010). Yet systemic risk of shareholder institutions is higher compared to that of cooperatives and NGOs (Di Bella, 2011). Therefore, we need to bear in mind that while an assumption might be true for one kind of MFIs, the same assumption could be violated for another kind of MFIs. Hence, it is vital to capture as much of the aforementioned differences as possible to avoid potentially biased conclusions (Louis, Seret, & Baesens, 2013). Therefore, in addition to consider the heterogeneity in regions, we separate MFIs based on their ownership structure/legal status and estimate their performance accordingly. We further elaborate the best practises for and delve into efficiency to better direct MFI investors and stakeholders.

The rest of this paper is structured as follow. The next section reviewed previous studies followed by an elaboration of the methods. the fourth chapter discusses the result. Finally, we present the concluding remark.

Literature Review

Beginning from Yaron (1994), the body of microfinance literature replete with performance evaluation. For the purpose of this study, we only focus on the studies that employed DEA or its closest parametric alternative, SFA. In global scale, the purpose of most literature has been studying the trade-off or discovering performance determinants. Haq et al. (2010) estimated financial and social DEA efficiencies in Africa, South Asia and Latin America and found no trade-off. It was contradicted, when including outreach as a driver of efficiency by Niels Hermes, Lensink, and Meesters (2009); N. Hermes, Lensink, and Meesters (2011) who used DEA and SFA estimations. Similarly, Annim (2012) used both methods and revealed conflicting evidence for trade-off. Annim (2012) discovered complementarity between the external environment (credit information, property rights and financial development) and MFIs' social efficiency. Hartarska and Mersland (2012) examined the impact of several governance mechanisms on MFIs' social outreach efficiency using SFA and found that efficiency increases with a board size of up to a certain threshold and decreases after that. They also found MFIs regulated by an independent bank are more efficient. The methodological gap in the aforementioned SFA studies was they applied one production/cost function for all MFIs in different regions. Bolli and Thi (2014) addressed this issue by comparing production processes across regions using SFA and found financial and social output reflect complements in South Asia but not in other regions.

Despite this correction, SFA studies are bound to specify a production function, which in most cases is based on unrealistic assumptions. An appealing property of the DEA approach is that multiple-input, multiple-output technologies can be modelled without behavioural assumptions and knowledge about cost/production function (Fall et al., 2018; Grifell-Tatje & Lovell, 1996), which makes it suitable for organisations with multiple objectives (Bowlin, 1998). However, most of microfinance DEA focused on specific regions/countries. For example, Gutiérrez-Nietoa et al. (2007) that studied MFIs in Latin America, Ben Soltan Bassem (2008) focused on MFIs in the Mediterranean, Piot-Lepetit and Nzongang (2014) investigated only village banks in Cameron and Mahinda Wijesiri et al. (2015) examined the best practices in Sri-Lanka.

The rarity of global studies that employed DEA is because the employed DEA models are unable to take into consideration the differences in social, physical and economic environmental in which the MFI works. This gap is overcome by DEA-Meta-frontier approach, as developed by (O'Donnell et al., 2008), in such a way that the efficiency of each MFI is measured relative to a common meta-frontier, defined as the boundary of an unrestricted technology set. Moreover, this model defines group frontiers to be the boundaries of restricted technology sets, where the restrictions derive from lack of economic infrastructure and/or other characteristics of the production environment.

Our study applied a similar method as Mahinda Wijesiri et al. (2017) that investigated the impact if size and age on the efficiency of MFIs using Meta-frontier and bootstrap (for sensitivity and bias correction); however, we add several contributions. First, Mahinda Wijesiri et al. (2017) considered the heterogeneity of MFIs only in different regions, while we establish multiple meta-frontiers that take into account heterogeneity in size, as confirmed by Ben Soltan Bassem (2008); Gregoire and Tuya (2006)), and type as proved by (Gutierrez-Nieto et al. (2007); Haq et al. (2010); Postelnicu and Hermes (2015)). Therefore, we delve into the inefficiency within different types and within different regions from multiple aspects.

Method

Sample homogeneity is one of the fundamental assumptions of frontier methods. It implies the efficiency of firms operating under different production technologies cannot be compared (O'Donnell et al., 2008). Battese, Rao, and O'donnell (2004) solved this issue for SFA models and later O'Donnell et al. (2008) elaborated the model for use in DEA framework. The Meta-frontier model developed by O'Donnell et al. (2008) is a function that envelops the individual group frontiers each having their specific technology and environmental factors, and provides consistent and homogeneous efficiency comparison (Wanke & Barros, 2016). O'Donnell et al. (2008) showed DEA meta-frontier has the ability to deal with issues such as technological change, time-varying inefficiency effects, and multiple outputs. The Meta-frontier is defined as the boundary of an unrestricted technology set.

Groups of firms that operate in resource-poor or highly regulated production environments may only have access to a restricted technology set. We refer to the boundaries of these restricted sets as group frontiers. Importantly, the meta-frontier envelops the group frontiers. Thus, efficiencies measured relative to the meta-frontier can be decomposed into two components: a component that measures the distance from an input–output point to the group frontier (the common measure of technical efficiency); and a component that measures the distance between the group frontier and the meta-frontier (representing the restrictive nature of the production environment). Estimates of technical efficiency are often used to design programs for performance improvement. These programs involve changes to the management and structure of the firm. Estimates of the gap between group frontiers and the meta-frontier can also be used to design programs for performance improvement, but these programs involve changes to the production environment, mainly macroeconomic tools or the MFI actions to change the production environment through relocation. The method is illustrated in Figure 1.

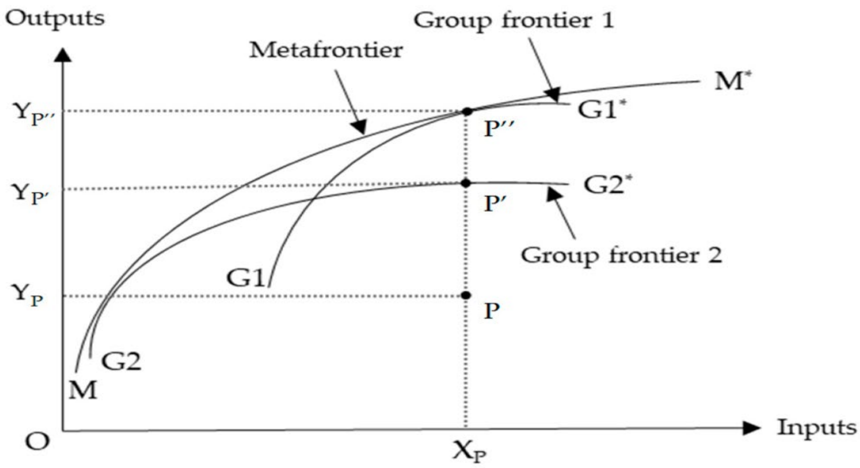

Figure 1 The Meta-frontier and group frontiers

A Meta-frontier was obtained by pooling the data of the two technologies and repeating the standard DEA. As shown in Figure 2, if MFI P belongs to Technology 1, the technical efficiency of the MFI P obtained in terms of group frontier is determined by the ratio of the distances $X_P P$ and $X_P P'$. On the other hand, the technical efficiency obtained in terms of the Meta-frontier is determined by the ratio of the distances $X_P P$and $X_P P''$. Even if the level of input is the same, MFI P may produce different outputs when operated under different technology.

The linear programming problem to be solved is

$$\max \emptyset$$

$$s.t.$$

$$\sum_{j=1}^{J} \lambda_j X_{mj} \leq X_m(P) \quad m = 1,2,\dots,M$$

$$\sum_{j=1}^{J} \lambda_j Y_{nj} \leq \emptyset Y_n(P) \quad n = 1,2,\dots,N$$

$$\sum_{j=1}^{J} \lambda_j = 1$$

$$\sum_{j=1}^{J} \lambda_j \geq 0 \quad j = 1,2,\dots,J$$

where the variables X_{mj} and Y_{nj}indicate the amount of input (m = 1, 2, … , M) and output (n = 1, 2, … , N) for each region/type, respectively (j = 1, 2, … , J ; P ∈ {1, 2, …, J}). N, M, and J are the number of output variables, the number of input variables, and the number of regions/types for the two Meta-frontiers.

The objective function of this optimization problem is to optimize the output improvement potential, Ø in both financial and social aspect. The value 1/Ø is interpreted as the technical efficiency, which means how far the MFI is located from its closest best practice on Meta-Frontier, which can be an MFI in different type and different region. This is called Meta-Technical Efficiency (MTE). On the other hand, the managerial efficiency (ME) is the distance from regional frontier.

The technology gap ratio (TGR) is an indicator of the gap between MFIs regional frontier and the Meta-frontier, noting that this is exactly the same as the program efficiency scores of (Charnes, Cooper, & Rhodes, 1981). Thus, the TGR is an indication of the differences in production possibilities between each region and the Meta-frontier, due to the variations in regional production environments. The technology gap ratio for MFI belonging to region/type k can be calculated as follows:

$$TGR_{ik} = \frac{MTE_i}{ME_i}$$

Note since $ME_i \leq MTE_i$, therefore, $TGR_{ik} \leq 1, \forall\, i.$

The closer the mean $TGR_{ik}$is to 1, the smaller the difference in production possibilities between the region and the meta-technology.

As explained, the estimation of the Meta-frontier applied DEA. However, DEA has several statistical limitations that might lead to incorrect or misleading results. For that, we use the 'Bootstrap' methodology of Simar and Wilson (2007). The model was used by Assaf, Barros, and Josiassen (2010); Mahinda Wijesiri et al. (2017)Because of space limitation, the technical details of the methodology are not provided here. Refer to Simar and Wilson (Simar & Wilson, 1998, 1999)

After this we use Kruskal–Wallis to test if the efficiencies relative to meta-frontier (MTE_i) among the regions are statistically difference, where the null hypothesis is that the mean ranks based on the MTE_i are the same in all the regions.

Moreover, the efficiency estimates may be sensitive to extreme values of input and output affecting the frontier. Thus, the super efficiency approach (Banker & Chang, 2006) has been used to identify and remove highly influential observations. In this study, MFIs with super efficiency score more than the sum of third quartile and one and half times of interquartile range [Q3 + 1.5(Q3-Q1)] are considered outliers (Bogetoft & Otto, 2011).

The Selection of inputs and outputs

Data of this study is obtained from the MIX (www.themix.org), which is the most common databases used in MFIs literature (Postelnicu & Hermes, 2015, 2018; Mahinda Wijesiri et al., 2015).

For the variable selection, we need to consider mathematical and theoretical requirements of DEA and microfinance. DEA framework identifies the non-dominated efficient DMUs in the data space spanned by inputs and outputs. So, too many inputs and outputs manifest as too many relatively efficient DMUs. Similarly, too few inputs and outputs cannot show the efficient DMUs. To select the right inputs and outputs, we follow past studies. One of the debates over variable selection in microfinance studies is the three approaches through which scholars consider an MFI as a formal financial sector; production, intermediation, and asset approach (Ben Soltane Bassem, 2014).

In the production approach, financial sector is using two main inputs of employees, capital expenditures (asset), and operating cost to produce loans and other financial services (e.g. savings, insurance) and more importantly, deposit for the clients (Kipesha, 2013). Deposit is, therefore, an output because of the value added including safekeeping, liquidity, and additional services to the account holders (Benston, Hanweck, & Humphrey, 1982). The intermediation approach refers to the match making of deposits and loans. Hence, deposit is considered as input in this approach, while it is an output in the production approach (N. Hermes et al., 2011). Under intermediation efficiency, microfinance institutions are considered as intermediary institutions, which collect funds from economic units with excess resources (Savers) and channels them to economic units with the deficit (borrowers) hence transferring the purchasing power from surplus units to deficit units in the society (Kipesha, 2013). Lastly, as financial institutions want to maximise loans to their clients, the market value of the total asset is considered one of the main outputs under the asset approach. Although the value of assets acts as output in this approach, loans/credit is the most important financial service that MFIs provides to their customers (N. Hermes et al., 2011).

Most of the past studies applied production approach as it is prevalently believed that most MFIs do not mobilise funds in terms of deposits (Ben Soltan Bassem, 2008; Mia & Chandran, 2016; Segun & Anjugam, 2013; Usman, 2011). We follow past studies and apply production approach. The inputs are assets and number of employees as applied by (Annim, 2012; Ben Soltan Bassem, 2008; Gutiérrez-Nieto, Serrano-Cinca, & Molinero, 2009; Haq et al., 2010; Niels Hermes et al., 2009; Mahinda Wijesiri & Meoli, 2015). Asset is defined as total wealth available to MFI from capital and borrowings for its transformation process. It is used as inputs to represent capital for production approach and number of employees are counted according to the part-time or full-time personnel who work at MFIs (Widiarto & Emrouznejad, 2015).

For the financial outputs we use financial revenue and gross loan portfolio similar with (Gutiérrez-Nieto et al., 2009; Gutiérrez-Nietoa et al., 2007; Lebovics, Hermes, & Hudon, 2016). The social outputs, depth and breadth of outreach are similarly selected following (Mia & Soltane, 2016; Postelnicu & Hermes, 2018; Widiarto & Emrouznejad, 2015). Depth of outreach specifies the capacity of projects to tackle the poverty of the poorest; and the latter measures the amplitude of the project (Bassem, 2008). For cross-country analysis, it is usually measured by average loan size per borrower divided by GNI per capita (DEPTH) (Postelnicu & Hermes, 2018) and number of active borrowers (NAB) as the measure of breadth of outreach, like (Widiarto & Emrouznejad, 2015; Mahinda Wijesiri et al., 2015)

Result

First, the correlation between the inputs and outputs are tested. According to the Pearson correlation represented in Table 1, there is no significant correlation within the inputs and within outputs. Unlike, parametric approaches multicollinearity does not cause any problem is DEA solution. In fact, the algorithm of DEA assign weights to each variable and gauge the efficiency accordingly. However, correlation test is recommended to insure the variables maintain an isotonic relationship and DEA model can provide a suitable predictive model (Golany & Roll, 1989). This means increasing the value of any input while keeping other factors constant should not decrease any output but should instead lead to an increase in the value of at least one output (Bowlin, 1998).

Table 1 Inputs and outputs correlation

	Asset	Personnel	Breadth	depth	GLP	FR
Asset	1.000	0.557	0.046	0.080	0.266	0.899
Personnel	0.557	1.000	0.167	0.010	0.000	0.574
Breadth	0.046	0.167	1.000	0.021	0.001	0.063
depth	0.080	0.010	0.021	1.000	0.003	0.043
GLP	0.266	0.000	0.001	0.003	1.000	0.361
FR	0.899	0.574	0.063	0.043	0.361	1.000

A general, yet simplistic picture of variables shows that financial revenue is significantly associated with the asset, while neither of social measures has a significant association with financial variables. Table 2 represents a summary of statistics of the variables. An average MFI in the world, has an asset of around $18million and 230 personnel. Employing the two main inputs, it provides financial services to almost 33’000 clients, with an average loan size that is 8 times larger than their income. Through this, the MFI makes a loan portfolio as big as $13million and earns a revenue of almost $5million a year. The large number of standard deviations show the wideness of MFIs range in terms of both inputs and financials and social outputs. This is another reason why, especially in global analysis, non-parametric analysis with no restrictions of normality distribution is advantageous.

Table 2 Summary of World’s Statistics

World(462)

	Assets	Personnel	NAB	Depth	GLP	Financial Revenue
min	116811	2	42	0.166	15459	26777.176
max	136382104	3491	567761	48.309	93773046	49275281
mean	17662554	229.705	32666.136	8.007	13860796	4481429.5
St-dev	23231278	355.618	61903.915	8.917	18333727	5968492.6

A closer look at each region, as summarised in Table 3, shows that the smallest MFI in terms of both number of employees and outreach is located in EU, followed by LAC with only 2 personnel and 42 active borrowers in EU and 3 personnel and 87 active borrowers in LAC). Moreover, the MFIs in LAC have the minimum average number of employees (123 personnel) followed by East Asia (126 personnel). MFIs in EU also has the lowest average number of active borrowers (just above 12'000), followed by LAC (126'000). Not surprisingly, the smallest financial revenue is also earned by an MFI in EU.

Despite the proximity in the minimum size of MFIs in Eastern Europe, Latin America and East Asia in terms of employees and outreach, in Africa and South Asia the smallest MFIs are at least 10 times larger in terms of number of employees and borrowers. MFIs in all regions, expect for SA, also have relatively similar minimum depth of outreach (the offered loan size is between 15%-28% of average national income per capita).

On the other hand, the largest MFI(s) is located in South Asia in terms of inputs, financial output and outreach with almost 3500 employees, offering loans to more than 550'000 clients and earning just above $30million. The second largest MFIs(s) exists in Africa.

On average, MFIs in South Asia has the highest number of personnel, 506 and active borrowers 94'000 and earns the highest average revenue, well above $5million. However, MFIs in LAC offers the largest loan size, which is above 11 times larger than national income per capita. The large number of standard deviations in all regions represents the diversity of MFIs in each region.

In summary, the summary statistics of regions show than the size of inputs and outputs of MFIs in EAP and EU are not comparable with that of MFIs in other regions. However, their efficiency is a matter of proper allocation of resources and optimization of their social and financial output, which is not as straightforward as variable analysis.

The convolution in regional financial and social performance is another riddle that is to be detangled by the result of DEA model in particular as multiple variables are considered simultaneously.

Table 3 regional summary of statistics

Africa and MENA (82) (Africa)						
	Assets	**Personnel**	**NAB**	**Depth**	**GLP**	**Financial Revenue**
min	624044	19	818	0.166	284443	169037.22
max	100224568	1144	151335	47.847	73440376	29039420
mean	20788110	262.329	28553.598	5.181	14653137	5238227.9
St-dev	23366755	258.693	34256.030	8.109	18322055	6481674.6
Eastern Europe and Central Asia (69) (EU)						
min	166940	2	42	0.286	109709	26777.176
max	111786373	1053	96832	33.898	83138685	24136532
mean	18335565	146.304	12311.667	4.622	14693780	4425329.5
St-dev	25603356	205.490	18116.896	5.753	20062337	5540247
East Asia and The Pacific (59) (EAP)						
min	123485	4	50	0.279	122759	51199.546
max	89968325	554	193733	42.194	74905255	16329251
mean	10175028	126.441	17478.814	7.680	7523508.1	2015012.4
St-dev	17334183	143.200	32270.633	8.509	13411657	3015479.2
Latin America and The Caribbean (158) (LAC)						
min	116811	3	87	0.238	15459	51069.769
max	87903184	836	89370	48.309	82611649	49275281
mean	13561915	123.285	12674.114	11.375	10821928	4437018.2
St-dev	16243357	147.197	16423.898	11.278	13569327	6151617.9
South Asia (94) (SA)						
min	357290	9	581	1.098	79610	38694.507
max	136382104	3491	567761	22.676	93773046	30563230
mean	26034168	506.160	94330.798	7.500	21643703	5485142.4
St-dev	30813191	616.732	108068.9	4.305	23592943	6556475.6

Table 4 illustrates the bootstrap average efficiency of each region relative to the group and Meta-frontier DEA. The bootstrap regional frontier is a representation of the state of knowledge or the technology that MFIs in the specific region use to transform inputs into financial and social outputs, whereas the bootstrap Meta-frontier implies the state of the knowledge or the technology at the global level. This means if the regional efficiency score of an MFI is high and its meta-frontier efficiency is low, the inefficiency is related to the environmental factors and lack of access to similar technology/infrastructure. Note that confidence intervals of 95 and 99% have been also computed for the group frontiers and the Meta-frontier model, and we confirmed that for every observation the bootstrap result lie inside the confidence intervals. The best representative of how much of the inefficiency is because of the lack of technological access is the technology gap ratio (TGR) which is the ratio of the group frontier score and the Meta-frontier (O'Donnell et al., 2008). This is also called the productivity potential (Battese et al., 2004).

Table 4 Regional Meta-frontier Results

Meta-frontier						
	Africa	EU	EAP	LAC	SA	World
min	0.242	0.362	0.298	0.410	0.370	0.242
max	1.000	1.000	0.850	1.000	1.000	1.000
mean	0.495	0.617	0.549	0.701	0.700	0.624
St-dev	0.208	0.101	0.056	0.295	0.224	0.120
Number (percentage) of fully efficient MFIs	3 (3.2%)	2 (2.9%)	0	5 (3.1%)	3 (3.1%)	13
Regional Frontier						
	Africa	EU	EAP	LAC	SA	World
min	0.310	0.491	0.302	0.490	0.473	0.310
max	1.000	1.000	1.000	1.000	1.000	1.000
mean	0.890	0.865	0.848	0.888	0.790	0.893
St-dev	0.099	0.160	0.100	0.197	0.191	0.152
Number (percentage) of efficient MFIs	18 (23%)	14 (20%)	12 (20%)	16 (12%)	10 (10%)	70 (15%)
TGR						
	Africa	EU	EAP	LAC	SA	World
min	0.285	0.406	0.492	0.290	0.512	0.285
max	1.000	1.000	1.000	1.000	1.000	1.000
mean	0.556	0.401	0.647	0.789	0.886	0.699
St-dev	0.098	0.109	0.120	0.269	0.221	0.138

A general look at the Meta and Group frontier efficiency scores show that in all regions the furthest away MFIs from the world frontier are only 24.2% efficient. This implies that the highest inefficiencies related to the technological possibilities is about 78%, which belongs, but not limited to some MFIs in East Asia. The high percent of inefficiency for the least efficient MFIs in all regions is seen in all of the five regions. Moreover, there is a consistency in the average efficiency scores in both Meta-frontier and group frontier as well as low standard-deviation in all regions that shows first a similar lack of access to best technological possibilities in all regions, which can be also proven through the fact that in each region maximum 5 (3.1% of) MFIs have access to the best productivity potential. The case is even worse for East Asia where no MFI is on the world frontier and has the lowest average Meta-frontier efficiency. East Asian MFIs have shown low efficiency/performance in other studies, too. For example, Haq et al. (2010) also mentioned that East Asian MFIs are less efficient than their peers in South Asia. Similarly, however, only in financial terms, Quayes (2015) found East Asian and African MFIs (as one group) has the lowest performance compared to the rest of the world.

Even the most efficient East Asian MFIs compared with the rest of the world is 15% less efficient that the bests in other regions. The average Meta-frontier efficiency, 0.549 shows that the maximum output that could be produced using the inputs and the technology of the EAP is just 55% of the maximum output that could be produced using the same inputs and the technology represented by the Meta-frontier. However, on the regional frontier there are 12 or 20% fully efficient MFIs. This is very similar to the proportion-wise statistics of Africa and Europe. More importantly, East Asia has the lowest standard deviation, which implies that the efficiency of MFIs in the region has less diversity both when they are compared with the other regions and within the region itself. This can be related to its comparatively small sample size. The average regional efficiency is 84.8%, which shows that MFIs in EAP transform almost 85% of their inputs into social and financial outputs using the infrastructure and technological capacities of the region. our average efficiency score and number of efficient MFIs is consistent with Kipesha (2012) that used a traditional CCR model of DEA and 35 MFIs found an average efficiency scores of 71%, 80% and 85% in East Asian MFIs for 2009 and 2010 and 2011. The number of best practices in the region is 12 MFIs, which is also consistent with the finding of also shows 5, 8 and 11 fully efficient MFIs in 2009 to 2011respectively.

To understand the part of inefficiency of the regions that is related to productivity potential/technological capacities we analyse the average technological Gap ratio (TGR). For EAP the TGR is 0.648, indicating that the maximum output that is feasible using the accessible technology by MFIs in EAP (and the input levels) is only about 64.8% of the output that could be achieved using the technology represented by the Meta-frontier. These MFIs are the world's best practices and are sparsely scattered in five regions.

The regional frontier, furthermore, depicted that even benchmarking towards a similar production frontier, only 15% of MFIs in the world are fully efficient. The majority of MFIs in all regions are relatively inefficient. Africa, however, has the highest number and percentage of fully efficient MFIs 18 MFIs, accounting for 23%. Our regional frontier result is in line with the findings of Bolli and Thi (2014) that Africa has the most efficient MFIs compared with East Asia/Pacific. However, the highest average efficiency is found in Latin American MFIs.

South Asia has the lowest number of fully efficient MFIs. The regional efficiency score of 0.790 implies that in South Asia on average 20% of the MFIs' inputs (personnel and assets) are wasted, due to mismanagement. The percentage of mismanagement waste/inefficiency in other regions, regardless of technology is less than 15%. Our results contradict the finding of Kabir and Benito (2009) that found South Asian MFIs have higher technical efficiency than Latin American and MENA MFIs. This shows how results can vary when technological heterogeneity amongst regions are taken into account. However, there are not many studies to which we can compare our results, as the performance has been prevalently measured through ratios or single variables in global level. Yet, Lafourcade, Isern, Mwangi, and Brown (2005) shows low financial efficiency for African MFIs and Tucker and Miles (2004) that found MFIs in the world have low financial efficiency.

Our results can be explained through the finding of Lapenu and Zeller (2002) that MFIs in SA and LAC receives the highest international support which makes the highest Meta-frontier efficiency score, and highest proportion of MFIs with access to best technologies, while a low regional score. In South Asia, in particular, it is clear that the access to best productivity potential is more or less provided, however the allocation of resources and managerial efficiency need to be improved. The opposite is the case for MFIs in Africa, MENA, East Asia and the Pacific. Compared with other regions, the lack of access to technological possibilities play a big role (Almost 50%) in their inefficiency.

The low meta-frontier efficiency for all regions shows despite the wide range of innovations and overcoming various constraints by MFIs, stable macroeconomic and institutional environments that facilitates international access to the utmost technological potential is a key to improve the efficiency of MFIs. Unstable economies, restricting regulations or governance or many other factors that is out of this study scope in each region are still obstacles for the reach of international facilities that are provided to a few MFIs. Moreover, it is worthwhile to note that our regional measures may not fully acknowledge the significance of country characteristics such as state macroeconomic environments (eg: complexities associated with inflation and interest rates, availability of interest rate ceilings), policy induced shocks and level of competition in domestic markets.

However, many studies have proven that MFIs regulatory status is also a critical factor of heterogeneity amongst MFIs for efficiency analysis (to name a few Abdelkader, Hathroubi, and Jemaa (2014); Ahlin, Lin, and Maio (2011); Desrochers and Lamberte (2003); Gregoire and Tuya (2006); Gutierrez-Nieto et al. (2007); Haq et al. (2010); Kablan et al. (2014); Kipesha (2012); Roy Mersland and Strøm (2009); Paxton (2007); Postelnicu and Hermes (2015); Servin et al. (2012); Mahinda Wijesiri and Meoli (2015). Therefore, to obtain more meaningful results that capture the difference MFIs types we complete our analysis with a meta-frontier study of MFIs with different regulatory status (i.e., banks, Cooperatives, credit unions, NBFIs and NGOs.).

Table 5 depicts the statistics of different MFIs regulatory status. There is not much diversity between the smallest MFIs in four types. Within all types, there is an MFI with less than 5 personnel and \$250’000 assets that provide services to less than 100 active borrowers and earn less than \$50’000 revenue. However, on average Non-Bank Financial Institutions (NBFIs) employ the largest number of staff (255), serve the most clients (almost 42’000) and earn the highest average revenue of just below \$6 million. In terms of the average revenue, banks and NBFIs are close, yet the average outreach of NBFIs is almost twice as much as the number of banks borrowers. The highest average depth of outreach (9 times bigger than national income) is provided by NGOs, followed by Credit Unions/cooperatives (8.2 times bigger than national income), whereas the average loan size provided by bank MFIs is only around 6 times bigger than the average national income.

Table 5 type-various summary of statistics

Banks (88)						
	Assets	Personnel	NAB	Depth	GLP	FR
min	241145	2	42	0.166	109709	38694.507
max	136382104	1572	193733	48.309	86611135	30563229.5
mean	22185186.24	238.045	21992.784	5.737	16335840.7	5461584.6
St-dev	29149037.42	312.555	35626.906	7.700	21798483.4	7333030.94
Credit Unions/Cooperatives (73)						
min	116811	3	50	0.177	115453	26777.176
max	79650352	1144	201570	41.841	65455235	49275281.5
mean	11953819.37	126.096	15782.562	8.200	8871183.45	3296236.3
St-dev	16925207.18	205.869	29171.288	9.434	13167067.8	6683995.6
NBFIs (129)						
min	123485	4	69	0.238	122759	52700.8
max	116180524	1430	434476	45.249	89331729	24136531.6
mean	21582058.12	254.636	41893.4496	7.973	17981218.3	5719860.88
St-dev	24819087.68	282.936	72440.478	9.759	19987010.7	5895060.82
NGOs (172)						
min	252118	3	87	0.286	15459	48059.424
max	113346145	3491	567761	47.846	93773046	28428455.7
mean	14831914.45	250.715	38372.139	9.113	11621861.5	3554149.17
St-dev	20000916.94	456.808	71721.440	8.486	16208573.4	4576697.8

The results of Bootstrap DEA for MFIs with different regulatory status in Table 6 show that there are the lowest meta-frontier and group efficiencies are seen in NGOs and microfinance banks. The least efficient banks and NGOs can increase their output by 75-80% if they access the best technologies and productivity potential. However, not all of the inefficiency is due to the lack of technological access. even in comparison with homogeneous MFIs, the least efficient MFIs are NGOs and banks that produce 42.4% and 49.9% of their output, meaning a large proportion of inefficiency is due to mismanagement. To be precise, for the aforementioned least efficient NGOs and banks this share is 38% and 40% (1-TGR).

Our Meta-frontier results contradicts the finding of Barry and Tacneng (2014) that NGOs have higher financial and social performance than banks and cooperatives in Sub-Saharan African MFIs amongst the sample of 39 MFIs across Africa, Asia and the Latin America. We have mixed results compared to Kabir and Benito (2009) that found banks and credit unions are more efficient than NGOs and NBFIs in LA, MENA and SA. Similar with our findings, Kipesha (2012) showed that, on average the banks and NBFIs were more relatively efficient compared to NGOs and Cooperatives while the country efficiency averages show that, Kenya and Rwanda had higher average efficiency scores for three years under constant return to scale while Tanzania and Uganda have higher average efficiency scores under variable return to scale. The study recommends that MFIs in the area should improve their efficiency by better allocation of input resources used and reduction of the amount of waste since most of the inefficiency was found to be technical in nature.

Table 6 Type Meta-Frontier results

Meta-Frontier					
	Banks	Credit Union/Cooperative	NBFIs	NGOs	World
Min	0.309	0.572	0.390	0.256	0.256
Max	1.000	1.000	1.000	1.000	1.000
Mean	0.768	0.820	0.871	0.783	0.834
St-dev	0.101	0.111	0.119	0.121	0.141
Number (percentage) of fully efficient MFIs	2	3	4	3	12
Group-Frontier					
	Banks	Credit Union/Cooperative	NBFIs	NGOs	World
Min	0.499	0.631	0.547	0.424	0.424
Max	1.000	1.000	1.000	1.000	1.000
Mean	0.890	0.901	0.912	0.849	0.890
St-dev	0.12	0.093	0.170	0.162	0.191
Number (percentage) of fully efficient MFIs	15	11	15	9	50
TGR					
	Banks	Credit Union/Cooperative	NBFIs	NGOs	World
Min	0.611	0.803	0.824	0.578	0.501
Max	1.000	1.000	1.000	1.000	1.000
Mean	0.863	0.899	0.955	0.922	0.937
St-dev	0.118	0.119	0.114	0.100	0.100

In total, there are 2 banks, 3 Credit Union/Cooperatives, 4 NBFIs and 3 NGOs with the access to the best productivity potential. Based on the average Meta-frontier efficiency results, NBFIs, followed by NGOs and Credit Union/Cooperatives have the highest average MF efficiency, while banks have the least efficiencies on MF.

In group frontiers, NGOs again show the least average efficiency (0.849) and the lowest number of efficient MFIs on the group frontier (only 9). This can be because NGO-MFIs are neither supervised nor regulated by any external authority and are encouraged to be self-regulated. Even though self-regulation includes the standard accounting and reporting practices to enhance the overall performance, many NGO-MFIs are ill equipped to deal with self-regulatory mechanisms. Also, it might be the result of mission's diversity. For example, most NGOs have an array of social goals whereas companies focus on a few selected development goals. Regulated MFIs such as NBFIs and Cooperatives are able to build a large part of their capital base through savings mobilization. Thus, they are able to expand their service range at the frontier while minimizing the dependence on donor funding, the information problems and issue of liquidity management (Mahinda Wijesiri et al., 2015).

When compared with other types, the profit orientation and regulatory are closely linked according to which the main sources of financing of NGOs and cooperatives are subsidies which imply no cost of financing. Therefore , the Financial performance may then be higher than in profit-orientated MFIs (Blanco-Oliver, Irimia-Dieguez, & Reguera-Alvarado, 2016). However, in our sample NGOs are not only the least efficient amongst other types, they also show the minimum average efficiency when compared to one another. This proves that large part of NGOs' inefficiency is linked to their poor allocation of their available resources.

The higher efficiency score of regulated MFIs can be because they have the possibility of obtaining deposits from their customers and access a cheap source of financing (R. Mersland & Strom, 2009). Savings mobilization can significantly help MFIs sustain in times of crisis and economic difficulties (Patten & Johnston, 2001). The higher performance of banks and Credit Union/Cooperative than NGOs is also found by Tchakoute-Tchuigoua (2010) and linked to the access of banks to local capital market. Niels Hermes and Hudon (2018) related this to the negative association between subsidies and financial performance as also claimed by Bogan (2012); Caudill, Gropper, and Hartarska (2009). However, in the end there is a mixed impact of subsidized funding on MFIs performance, especially separating financial and specially performance (Niels Hermes & Hudon, 2018) and it might be associated to the level of subsidies (Hudon & Traca, 2011), which is out of the scope of this study.

Conclusion:

The popularity of microfinance has attracted a great deal of attention and money, and it has prompted investors, traditional donors, and governments to find sets of mechanisms that make MFIs make the best of their scarce resources. Majority of performance studies in global scale, only focused on the impact of one or few factors on financial or social performance. There are, however, some studies that evaluated the efficiency of small sample of MFIs (either in one/few regions or types). This scarcity has been essentially associated to the heterogeneity of MFIs that violates the assumptions of econometrics and other traditional methods.

We introduce a simple approach that accommodates the heterogeneity in regulate status and regional factors. Using DEA Meta-frothier analysis combined with bootstrap method, we contribute to this endeavour and overcome the statistical limitations and analysed the efficiency of 462 MFIs across the globe in 2015.

Local governments, international agencies, donors and the institutions themselves need to understand the share of inefficiency that is about regulatory status and location limitations and the share of mismanagement in allocation of resources. Especially as the global integrations of MFIs is leading to the spread of multi-national MFIs, while the inefficiency of some MFIs is not about environmental factors and introducing international competition might lead to huge waste of financial and human resource.

Moreover, the dynamism in the sector is leading many MFIs to shift to a different legal status. Regulation can be considered as a burden than a booster for an MFI whose inefficiency is more apparent within its group of similar types MFIs than compared with MFIs from other types. Therefore, our analysis has important consequences for researchers, investors, and practitioners. Research-wise, our results demonstrate that the inefficiencies found in the literature may to quite some extent be rational and result from comparing MFIs to a benchmark that is not in line with their main heterogeneities. For example, a non-profit MFI that is not very profitable, but maximizes its depth and breadth of outreach, will be very inefficient when assessed relative to a bank, and highly efficient when compared with a cooperative. Moreover, the findings of this study may provide some insights to the policy makers to develop appropriate policies in order to streamline the microfinance operations for their focus type and location of MFIs. Moreover, since both dimensions of efficiency determines the yardstick of efficiency, it puts pressure on the inefficient MFIs to come up to speed and put more effort into exploiting available resources to serve the poor in a financially sustainable way and learn from not only their peers with the same regulation, also in other groups. Donors and states, on the other hand, could use the benchmarking results for their funding decisions.

References

Abdelkader, I. B., Hathroubi, S., & Jemaa, M. M. B. (2014). Microfinance Institutions' Efficiency in the MENA region: a Bootstrap-DEA approach. *Research Journal of Finance and Accounting, 5*(6), 179-191.

Ahlin, C., Lin, J., & Maio, M. (2011). Where does microfinance flourish? Microfinance institution performance in macroeconomic context. *Journal of Development Economics, 95*(2), 105-120.

Annim, S. K. (2012). Microfinance efficiency: trade-offs and complementarities between the objectives of microfinance institutions and their performance perspectives. *The European Journal of Development Research, 24*(5), 788-807.

Assaf, A., Barros, C. P., & Josiassen, A. (2010). Hotel efficiency: A bootstrapped metafrontier approach. *International Journal of Hospitality Management, 29*(3), 468-475.

Ault, J. K., & Spicer, A. (2009). Does one size fit all in microfinance? New directions for academic research. In *Moving Beyond Storytelling: Emerging Research in Microfinance*: Emerald Group Publishing Limited.

Awoyemi, B. O., & Jabar, A. A. (2014). Prime lending rates and the performance of microfinance banks in Nigeria. *European Journal of Business and Management, 6*(12), 131-136.

Banker, R. D., & Chang, H. (2006). The super-efficiency procedure for outlier identification, not for ranking efficient units. *European Journal of Operational Research, 175*(2), 1311-1320.

Barry, T. A., & Tacneng, R. (2014). The impact of governance and institutional quality on MFI outreach and financial performance in Sub-Saharan Africa. *World Development, 58*, 1-20.

Bassem, B. S. (2008). Efficiency of microfinance institutions in the Mediterranean: an application of DEA. *Transition Studies Review, 15*(2), 343-354.

Bassem, B. S. (2014). Total factor productivity change of MENA microfinance institutions: A Malmquist productivity index approach. *Economic Modelling, 39*, 182-189.

Battese, G. E., Rao, D. P., & O'donnell, C. J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of productivity analysis, 21*(1), 91-103.

Benston, G. J., Hanweck, G. A., & Humphrey, D. B. (1982). Scale economies in banking: A restructuring and reassessment. *Journal of money, credit and banking, 14*(4), 435-456.

Blanco-Oliver, A., Irimia-Dieguez, A., & Reguera-Alvarado, N. (2016). Prediction-oriented PLS path modeling in microfinance research. *Journal of business research, 69*(10), 4643-4649. Retrieved from <Go to ISI>://WOS:000381533000074

Bogan, V. L. (2012). Capital Structure and Sustainability: An Empirical Study of Microfinance Institutions. *Review of Economics and Statistics, 94*(4), 1045-1058. Retrieved from <Go to ISI>://WOS:000311087800014

Bogetoft, P., & Otto, L. (2011). Additional topics in DEA. In *Benchmarking with DEA, SFA, and R* (pp. 115-153): Springer.

Bolli, T., & Thi, A. V. (2014). Regional differences in the production processes of financial and social outputs of microfinance institutions. *Economics of Transition, 22*(3), 461-495.

Bos, J. W. B., & Millone, M. (2015). Practice What You Preach: Microfinance Business Models and Operational Efficiency. *World Development, 70*, 28-42.

Bowlin, W. F. (1998). Measuring performance: An introduction to data envelopment analysis (DEA). *The Journal of Cost Analysis, 15*(2), 3-27.

Caudill, S. B., Gropper, D. M., & Hartarska, V. (2009). Which Microfinance Institutions Are Becoming More Cost Effective with Time ? Evidence from a Mixture Model. *Journal of Money Credit and Banking, 41*(4), 651-672.

Charnes, A., Cooper, W. W., & Rhodes, E. (1981). Evaluating program and managerial efficiency: an application of data envelopment analysis to program follow through. *Management science, 27*(6), 668-697.

D'Espallier, B., Goedecke, J., Hudon, M., & Mersland, R. (2017). From NGOs to banks: Does institutional transformation alter the business model of microfinance institutions? *World Development, 89*, 19-33.

Desrochers, M., & Lamberte, M. (2003). Efficiency and Expense Preference in Philippines' Cooperative Rural Banks.

Di Bella, M. G. (2011). *The Impact of the Global Financial Crisison Microfinance and Policy Implications*: International Monetary Fund.

Fall, F., Akim, A. M., & Wassongma, H. (2018). DEA and SFA research on the efficiency of microfinance institutions: A meta-analysis. *World Development, 107*, 176-188. doi:10.1016/j.worlddev.2018.02.032

Golany, B., & Roll, Y. (1989). An application procedure for DEA. *Omega, 17*(3), 237-250.

Gregoire, J. R., & Tuya, O. R. (2006). Cost efficiency of microfinance institutions in Peru: A stochastic frontier approach. *Latin American Business Review, 7*(2), 41-70.

Grifell-Tatje, E., & Lovell, C. K. (1996). Deregulation and productivity decline: The case of Spanish savings banks. *European Economic Review, 40*(6), 1281-1303.

Griffin, D., & Husted, B. W. (2015). Social sanctions or social relations? Microfinance in Mexico. *Journal of business research, 68*(12), 2579-2587.

Gutierrez-Nieto, B., Serrano-Cinca, C., & Molinero, C. M. (2007). Microfinance institutions and efficiency. *Omega, 35*(2), 131-142.

Gutiérrez-Nieto, B., Serrano-Cinca, C., & Molinero, C. M. (2009). Social efficiency in microfinance institutions. *Journal of the Operational Research Society, 60*(1), 104-119. Retrieved from <Go to ISI>://WOS:000261718500012

Gutiérrez-Nietoa, B., Serrano-Cincaa, C., & Molinero, C. M. (2007). Microfinance institutions and efficiency. *Omega-International Journal of Management Science, 35*(2), 131-142. Retrieved from <Go to ISI>://WOS:000241089300001

Haq, M., Skully, M., & Pathan, S. (2010). Efficiency of microfinance institutions: A data envelopment analysis. *Asia-Pacific Financial Markets, 17*(1), 63-97.

Hartarska, V., & Mersland, R. (2012). Which Governance Mechanisms Promote Efficiency in Reaching Poor Clients? Evidence from Rated Microfinance Institutions. *European Financial Management, 18*(2), 218-239. Retrieved from <Go to ISI>://WOS:000301533400003

Hermes, N., & Hudon, M. (2018). Determinants of the performance of microfinance institutions: A systematic review. *Journal of economic surveys, 32*(5), 1483-1513.

Hermes, N., Lensink, R., & Meesters, A. (2009). *Financial development and the efficiency of microfinance institutions*. SSRN.

Hermes, N., Lensink, R., & Meesters, A. (2011). Outreach and Efficiency of Microfinance Institutions. *World Development, 39*(6), 938-948. Retrieved from <Go to ISI>://WOS:000292345900006

Hosen, M. Z., Rahman, M. T., & Dutta, K. D. (2013). Risk adjusted performance analysis of NBFIs in Dhaka Stock Exchange. *Risk, 4*(13).

Hudon, M., & Traca, D. (2011). On the Efficiency Effects of Subsidies in Microfinance: An Empirical Inquiry. *World Development, 39*(6), 966-973. Retrieved from <Go to ISI>://WOS:000292345900008

Kabir, H., & Benito, S. (2009). Efficiency analysis of microfinance institutions in developing countries. *Networks Financial Institute*.

Kablan, S., Ayadi, O. F., Williams, J., Hyman, L., Nawaz, A., & Anduanbessa, T. (2014). Microfinance efficiency in West African Economic and Monetary Union (WAEMU): have reforms promoted sustainability or outreach? *Savings and Development, 38*(1), 89-111.

King'ori, S., Kioko, W., & Shikumo, H. (2017). Determinants of financial performance of microfinance banks in Kenya. *Research Journal of Finance and Accounting, 8*(16), 1-8.

Kipesha, E. F. (2012). Efficiency of microfinance institutions in East Africa: A data envelopment analysis. *European Journal of Business and Management, 4*(17), 77-88.

Kipesha, E. F. (2013). Production and intermediation efficiency of microfinance institutions in Tanzania. *Research Journal of Finance and Accounting, 4*(1), 149-159.

Lafourcade, A.-L., Isern, J., Mwangi, P., & Brown, M. (2005). Overview of the outreach and financial performance of microfinance institutions in Africa. *Microfinance Information eXchange, Washington, DC. http://www. mixmarket. org/medialibrary/mixmarket/Africa_Data_Study. pdf*.

Lapenu, C., & Zeller, M. (2002). Distribution, growth, and performance of the microfinance institutions in Africa, Asia and Latin America: A recent inventory. *Savings and Development*, 87-111.

Lebovics, M., Hermes, N., & Hudon, M. (2016). Are Financial and Social Efficiency Mutually Exclusive? A Case Study of Vietnamese Microfinance Institutions. *Annals of Public and Cooperative Economics, 87*(1), 55-77.

Louis, P., Seret, A., & Baesens, B. (2013). Financial efficiency and social impact of microfinance institutions using self-organizing maps. *World Development, 46*, 197-210.

Mersland, R., & Strom, R. O. (2009). Performance and governance in microfinance institutions. *Journal of Banking & Finance, 33*(4), 662-669. Retrieved from <Go to ISI>://WOS:000264391900008

Mersland, R., & Strøm, R. Ø. (2009). Performance and governance in microfinance institutions. *Journal of Banking & Finance, 33*(4), 662-669.

Mersland, R., Zamore, S., Ohene Djan, K., & Sommeno, T. (2019). Internationalization of the microfinance industry. In (pp. 139-149).

Mia, M. A., & Chandran, V. (2016). Measuring Financial and Social Outreach Productivity of Microfinance Institutions in Bangladesh. *Social Indicators Research, 127*(2), 505-527. Retrieved from <Go to ISI>://WOS:000376117000002

Mia, M. A., & Soltane, B. I. B. (2016). Productivity and its determinants in microfinance institutions (MFIs): Evidence from South Asian countries. *Economic Analysis and Policy, 51*, 32-45.

O'Donnell, C. J., Rao, D. P., & Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical economics, 34*(2), 231-255.

Patten, R. H., & Johnston, D. E. (2001). Microfinance success amidst macroeconomic failure: The experience of Bank Rakyat Indonesia during the East Asian crisis. *World Development, 29*(6), 1057-1069.

Paul, G. D., Ebelechukwu, E. C., & Yakubu, S. (2015). Impact of corporate governance on financial performance of microfinance banks in north central Nigeria. *International Journal of Humanities Social Sciences and Education, 2*(1), 153-170.

Paxton, J. (2007). Technical Efficiency in a Semi-Formal Financial Sector: The Case of Mexico. *Oxford Bulletin of Economics and Statistics, 69*(1), 57-74.

Piot-Lepetit, I., & Nzongang, J. (2014). Financial sustainability and poverty outreach within a network of village banks in Cameroon: A multi-DEA approach. *European Journal of Operational Research, 234*(1), 319-330. Retrieved from <Go to ISI>://WOS:000330148600028

Postelnicu, L., & Hermes, N. (2015). Microfinance Performance and Informal Institutions: A Cross-country Analysis. *Working Papers CEB, 15*.

Postelnicu, L., & Hermes, N. (2018). Microfinance performance and social capital: A cross-country analysis. *Journal of Business Ethics, 153*(2), 427-445.

Quayes, S. (2015). Outreach and performance of microfinance institutions: a panel analysis. *Applied Economics, 47*(18), 1909-1925. Retrieved from <Go to ISI>://WOS:000348756500007

Rhyne, E., & Otero, M. (2006). *Microfinance through the next decade: Visioning the who, what, where, when and how*: ACCION International Boston, MA.

Segun, K. R. S., & Anjugam, M. (2013). Measuring the Efficiency of Sub-Saharan Africa's Microfinance Institutions and its Drivers. *Annals of Public and Cooperative Economics, 84*(4), 399-422.

Servin, R., Lensink, R., & Van den Berg, M. (2012). Ownership and technical efficiency of microfinance institutions: Empirical evidence from Latin America. *Journal of Banking & Finance, 36*(7), 2136-2144.
Simar, L., & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management science, 44*(1), 49-61.
Simar, L., & Wilson, P. W. (1999). Of course we can bootstrap DEA scores! But does it mean anything? Logic trumps wishful thinking. *Journal of productivity analysis, 11*(1), 93-97.
Singh, R., Mahapatra, B., Mukherjee, K., & Bhar, C. (2014). Application of DEA for performance evaluation of Indian microfinance institutions. *ASIAN JOURNAL OF MANAGEMENT RESEARCH, 4*(3).
Tchakoute-Tchuigoua, H. (2010). Is there a difference in performance by the legal status of microfinance institutions? *The quarterly review of economics and finance, 50*(4), 436-442.
Tucker, M., & Miles, G. (2004). Financial performance of microfinance institutions: a comparison to performance of regional commercial banks by geographic regions. *Journal of Microfinance/ESR Review, 6*(1), 4.
Usman, A. (2011). *Efficiency Analysis of Micro-finance Institutions in Pakistan*. Retrieved from https://mpra.ub.uni-muenchen.de/34215/
Wanke, P., & Barros, C. P. (2016). Efficiency drivers in Brazilian insurance: A two-stage DEA meta frontier-data mining approach. *Economic Modelling, 53*, 8-22.
Widiarto, I., & Emrouznejad, A. (2015). Social and financial efficiency of Islamic microfinance institutions: A data envelopment analysis application. *Socio-Economic Planning Sciences, 50*, 1-17.
Wijesiri, M. (2016). Weathering the storm: ownership structure and performance of microfinance institutions in the wake of the global financial crisis. *Economic Modelling, 57*, 238-247. Retrieved from <Go to ISI>://WOS:000378667100019
Wijesiri, M., & Meoli, M. (2015). Productivity change of microfinance institutions in Kenya: A bootstrap Malmquist approach. *Journal of Retailing and Consumer Services, 25*, 115-121.
Wijesiri, M., Viganò, L., & Meoli, M. (2015). Efficiency of microfinance institutions in Sri Lanka: a two-stage double bootstrap DEA approach. *Economic Modelling, 47*, 74-83.
Wijesiri, M., Yaron, J., & Meoli, M. (2017). Assessing the financial and outreach efficiency of microfinance institutions: Do age and size matter? *Journal of Multinational Financial Management, 40*, 63-76.
Yaron, J. (1994). Successful rural finance institutions. *Finance and Development, 31*(1), 32.