Drivers of financial and operational efficiency of MFIs: empirical evidences from Eastern Europe and Central Asia

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Abstract

Purpose – The study attempts to examine the bias-adjusted financial and operational efficiency estimates of microfinance institutions (MFIs) operating in the Eastern Europe and Central Asia (ECA) region during the financial year 2017–2018. In addition, the study also identifies the responsible factors determining the financial and operational performances of MFIs operating in the ECA region.

Design/methodology/approach – The study employs two-stage bootstrap data envelopment analysis (DEA). In the first stage, the authors incorporate the bootstrap procedure in the DEA framework as suggested by Simar and Wilson (2000) to estimate the bias-corrected efficiency scores of 67 sample MFIs. In order to identify the drivers of efficiency level, the study deploys the bootstrap truncated regression model following the Simar and Wilson (2007) guidelines in the second stage of analysis.

Findings – The authors note from the empirical results that MFIs operating in the ECA region are relatively more financially efficient (0.588) than socially efficient (0.496). However, none of the MFIs were found to be operating at best-practice frontier while considering the bias-adjusted efficiency estimates. Further, the results of second stage of analysis confirm that corporate governance, that is, board size has positive and statistically significant impact on MFIs' performances. In addition, the bad credit quality deteriorates both financial revenue and operational efficiency. Moreover, the MFIs' size, profit status and debt-to-equity ratio were also found to be statistically significant to determine the operational and financial efficiency of MFIs in the ECA region.

Practical implications – The study provides the robust efficiency estimates and factors responsible to determine the financial and operational efficiency of MFIs operating in the ECA region. Further, the empirical results of the study provide the inputs and further direction to the policymakers, regulators, practitioners and managers in framing the policy and optimal operating strategies for ECA MFIs industry.

Originality/value – The study extends the DEA analysis by incorporating the bootstrap procedure in DEA model to estimate the bias-adjusted efficiency scores which are more reliable and robust. In addition, bootstrap truncated regression has been applied to identify the drivers of efficiency. Moreover, in the literature there is no single study which has deployed the double bootstrap DEA framework to examine the financial and operational efficiency estimates and its drivers.

Keywords Financial efficiency, Operational efficiency, Bootstrap DEA, Bootstrap truncated regression, Microfinance institutions, Eastern Europe and Central Asia

Paper type Research paper

1. Introduction

Microfinance is the special type of services offered by microfinance institutions (MFIs), which mainly focusses on to serve the poor, unbanked and/or under-banked population

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around the world (Servin *et al.*, 2012). It has been considered as one the significant devices of the poverty alleviation programmes (Widiarto and Emrouznejad, 2015). The microfinance empowers the women and poor and helps them in building financial assets and reduces the economic vulnerability. Besides, the MFIs specifically focus on promoting self-employment and entrepreneurship activities (Hartarska, 2005; Daher and Le Saout, 2017). In addition, the United Nations has declared the year 2005 as "The International Year of Microfinance", to recognise the importance of microfinance. Till the year 2010, the MFIs had served 200m poor worldwide (Reed, 2015). As per MIX Market report 2017–2018, globally, the reported MFIs have gross loan portfolio of US$112bn at the end of financial year 2017, which recorded a growth of 14.30% from the previous financial year 2016. Further, the number of active borrowers grew to 112m and registered a year-over-year growth rate of 9.80%. It is worth mentioning here that the MFIs operate to achieve the dual goals: financial efficiency and social outreach (Gutiérrez-Nieto *et al.*, 2009). Since the MFIs serve financial service to the poor (social outreach, i.e. original mission of microfinance), which are generally scattered in the remote areas, consequently, the MFIs need to incur the high operating cost to serve their small financial needs (Khan and Gulati, 2019). Particularly, these MFIs need to earn enough financial revenue to be operationally efficient to offer the finance at the lowest possible cost of per dollar lent (Gutiérrez-Nieto *et al.*, 2009). Therefore, the MFIs need to financially and operationally efficient to sustain in the long run while achieving their dual goals of performance.

The microfinance in the Eastern Europe and Central Asia (hereafter ECA) region has started in the mid of 1990s. The MFIs industry in the ECA region works very closely with the traditional financial system. These MFIs are very large in size (KazMicroFinance, Credo and Mikrofin, etc.) and their asset size is comparable with the mainstream financial service providers. The MFIs of ECA region are different in many aspects in comparison with MFIs operating in other countries of the world (Caudill *et al.*, 2009). Further, the MFIs in the ECA are heavily dependent on subsidy from the donors (Caudill *et al.*, 2009). In addition, Caudill *et al.* (2009) argued that the lower subsidy is associated with the higher cost inefficiency of these MFIs. However, during the recent year, the donors are withdrawing the subsidies, competition is increasing and commercialisation in the MFIs is taking place, and hence, the MFIs industry needs to be financially and operationally efficient. During the recent decades, in the empirical efficiency literature, the studies which have assessed the efficiency of MFIs have grown in numbers (see Fall *et al.*, 2018). However, there are only a few studies which have attempted to examine the efficiency of MFIs operating in the ECA region. Hartarska (2005) has assessed the performance of MFIs operating in the Central and Eastern Europe and the Newly Independent States. However, the author has focussed on the governance impact on performance. In addition, Caudill *et al.* (2009) have investigated whether with time the ECA MFIs became cost-effective or not. To the best of the authors' knowledge, no study has been found to examine the bias-corrected financial and operational efficiency scores of MFIs in the ECA region using data envelopment analysis (DEA) framework. Therefore, we are motivated to measure the efficiency of MFIs operating in the ECA regions and identify what are the responsible factors to determine MFIs' performance. Therefore, an assessment of financial and operational efficiency of MFIs and factors responsible for determining efficiency levels would provide the inputs and further direction to the policymakers, regulators, practitioners in framing the appropriate policy and optimal operating strategies for ECA MFIs industry.

Against this backdrop, the study attempts to measure the bias-corrected operational and financial efficiency of MFIs operating in the ECA region during the year 2017–2018. In addition, the study also identifies the possible factors which drive the efficiency level. In particular, the widely used conventional DEA models do not provide the reliable efficiency estimates. Further, these scores used in the second stage of analysis (i.e. regression analysis) may mislead the authors by offering the biased and inconsistent estimates (Simar and Wilson, 2007). Therefore, to address the particular issue, we incorporated the bootstrap procedure in the DEA framework as suggested by Simar and Wilson (2007) to assess the bias-corrected efficiency estimates of individual MFIs. Further, in the second stage of analysis, the study has adopted the bootstrap truncated regression model recommended by Simar and Wilson (2007) to identify the factors affecting the operational and financial performance of MFIs operating in the ECA region.

The study contributes in the empirical efficiency literature in the following ways. First, to the best of the author's knowledge, there is no study which measured the operational and financial performance of MFIs operating in the ECA region. In particular, the present study assesses the bias-corrected financial and operational efficiency of individual MFIs. Second, the conventional DEA models do account for the bias and, consequently, overestimate the efficiency scores. Therefore, to overcome this issue, the study incorporated the bootstrap procedure in DEA model to separate the bias from the efficiency estimates. Third, the study has constructed the two separate DEA models in order to examine the operational and financial efficiency scores. Fourth, the study identified the factors which affect the performance of MFIs. Therefore, we designed two regression equations to identify the determinants of operational and financial efficiency estimates. In particular, the study deployed the bootstrap truncated regression analysis as suggested by Simar and Wilson (2007) in the second stage of analysis to identify the drivers of efficiency estimates.

The rest of the study unfolds as follows. Section 2 briefs on the overview of microfinance sector in the ECA region. Section 3 consists of relevant literature review. Section 4 explains the methodology used and briefs on inputs and outputs incorporated in the DEA model. Empirical findings are reported in section 5, and the discussion based on the empirical findings has been presented in section 6. Conclusions along with the managerial implications have been reported in the final section.

2. An overview of microfinance sector in the ECA region

Over the recent decades, the microfinance has been considered as one of the significant tools to eradicate poverty and nurture the economic development particularly in the developing parts of the world. The microfinance is the provision of small credit to lower-income people, small entrepreneurs and households, to smooth the daily consumption and generating income which reduces the vulnerability and enhances the overall living standards of the poor.

The microfinance in the ECA region is mainly offered by following types of financial institutions: credit unions/cooperatives, NGOs, microfinance banks and commercial banks (downscaling). As per the Global Outreach and Financial Performance Benchmark Report – 2017–2018, the reported 87 financial service providers (FSP) reached 18.40m borrowers with US$19.29bn gross loan portfolio in the ECA region. Besides, the ECA MFIs industry has mobilised US$3.98bn deposits from 4.36m depositors at the end of financial year 2017. Among the ECA nations, Mongolia serves the largest number of borrowers, for example, 0.50m, followed by Tajikistan (0.314), Kyrgyzstan (0.261), Georgia (0.247) and Azerbaijan (0.207).

Further, the ECA MFIs industry has unique characteristics; the region has the lowest share of female borrowers (i.e. 49%) in the total number of active borrowers, which is even lower than that in the Middle East and North Africa (MENA) which have 60% shares of women in the total borrowers. Among all the regions, the operating costs are very high in ECA region which is evident from the cost per borrower US$198.10, which is relatively very high in the global microfinance industry. Moreover, this cost is US$32.70 only in the South Asian region which is the most cost-effective in the world. Further, the credit quality remains the centre of the discussion in the ECA microfinance industry. During the financial year 2017, portfolio at risk for 30 days was at 15.10% (MIX Market report 2017–2018). This is the worst credit quality ever reported by MIX Market in the MFIs operating in the ECA region. Moreover, the higher operating expenses, lower staff productivity and bad credit quality and lower female participation are the major obstacles in the growth of the microfinance sector in the ECA region. However, regulators have taken the corrective measures timely, and as a result, stability in the lending mechanism and improvement in the loan repayment rates were observed.

3. An empirical literature on MFIs' efficiency

This section reviews the existing empirical MFIs' efficiency literature. We found that the focus of academicians on assessing the MFIs' efficiency has increased over the last decade; however, the MFIs' efficiency literature requires more quality research work to flourish further. Many authors have contributed in the microfinance empirical efficiency literature with the quality of research work (e.g. Gutiérrez-Nieto *et al.*, 2007; Bassem, 2008; Gutiérrez-Nieto *et al.*, 2009; Haq *et al.*, 2010; Masood and Ahmad, 2012; Alinsunurin, 2014; Piot-Lepetit and Nzongang, 2014; Widiarto and Emrouznejad, 2015; Wijesiri *et al.*, 2015; Kaur, 2016; Lebovics *et al.*, 2016; Wijesiri *et al.*, 2017; Kumar and Sensarma, 2017; Khan and Gulati, 2019; Collins, 2019). In addition, the majority of the studies have employed the conventional frontier methods to examine the performance of MFIs (Khan and Gulati, 2019). Moreover, both the DEA and SFA (stochastic frontier analysis) are frequently used in the MFIs' empirical efficiency literature (Fall *et al.*, 2018). However, the embryonic MFIs' efficiency literature requires more quality research work to flourish further.

Gutiérrez-Nieto *et al.* (2007) examined the efficiency of 30 MFIs operating in Latin American countries by using DEA model. The empirical results suggest that the level of efficiency achieved by an MFI depends on the chosen input–output specifications. Bassem (2008) assessed efficiency level of 35 MFIs operating in Mediterranean zone for the years 2004 and 2005. Gutiérrez-Nieto *et al.* (2009) examined the efficiency of 89 MFIs operating in Asia, Africa, Latin America and Eastern Europe in the financial year 2003. They employed CCR-DEA model with an assumption of constant returns to scale to obtain financial and social efficiency estimates of the sampled MFIs. Haq *et al.* (2010) estimated the cost efficiency of 39 MFIs operating in Africa, Asia and Latin America region. Using DEA approach, Alinsunurin (2014) examined the efficiency of 41 Philippine MFIs. The study analysed the efficiency differences across the NGO and non-NGO-based MFIs operating in the year 2011. Piot-Lepetit and Nzongang (2014) scrutinised the relationship between the social and financial performances of 52 MFIs operating in Cameroon during the financial year 2009. Further, Widiarto and Emrouznejad (2015) compared the performance of 231 conventional and Islamic MFIs operating in MENA, East Asia–Pacific and South Asia regions during the period 2009–2010. They employed output-oriented meta-frontier-based DEA model to assess the financial, social and overall efficiencies of sampled MFIs. In addition, Lebovics *et al.* (2016) examined the trade-off in the dual objectives of 28 Vietnamese MFIs operating in the year 2011. They employed DEA to measure the efficiency scores and did not find any evidence to support trade-off. Besides, Kaur (2016) assessed the efficiency of 81 Indian MFIs for the year 2012 and found that there was no trade-off in achieving efficiency and sustainability. More recently, Kumar and Sensarma (2017) used a period from 2004 to 2011 to examine the efficiency and outreach of 75 MFIs from India.

After thorough review of literature, we found only few studies which assess the performance of MFIs operating in the ECA region (Hartarska, 2005; Caudill *et al.*, 2009). Hartarska (2005) has assessed the performance of MFIs operating in the Central and Eastern Europe and the Newly Independent States. However, the author has focussed on the governance impact on performance. Besides, Caudill *et al.* (2009) have investigated whether with time the ECA MFIs became cost-effective or not. Apart from three or two studies, to the best of my knowledge, no study has found to examine the efficiency of ECA-based MFIs.

In the literature, most of the studies have used the conventional DEA or SFA models which generally provide the biased efficiency estimates and may mislead the authors (Simar and Wilson, 2007). Only a few studies have applied the bootstrap procedure to assess the bias-corrected efficiency scores, for instance, Wijesiri *et al.* (2015) identify the determinants of technical efficiency for 36 Sri Lankan MFIs using the double bootstrap DEA approach. Bibi *et al.* (2017) for South Asian MFIs have used the bootstrap procedure in DEA to examine the bias-corrected efficiency estimates. More recently, Khan and Gulati (2019) have employed the bootstrap DEA model to assess the bias-corrected financial and social efficiency of 82 Indian MFIs. They also used bootstrap truncated regression model to identify the performance determinants. However, in the ECA MFIs' efficiency literature, no study has measured the bias-corrected efficiency of MFIs by deploying the bootstrap DEA models.

In sum, to fill the gaps in the literature, the present study attempts to estimate the financial and operational efficiency of MFIs operating in ECA region. To assess bias-corrected efficiency estimates, we incorporated the bootstrap procedure in the DEA framework as suggested by Simar and Wilson (2007). Further, we extended the analysis to explore the performance determinants. In order to identify the factor determining the financial and operational efficiency, we designed two separate regression equations. Further, we applied the bootstrap truncated regression in the second stage as directed by Simar and Wilson (2007) to draw valid inference from the results.

4. Methodological framework

This section explains the methodology used in the present study. We assessed the bias-corrected financial and operational efficiency estimates of individual sampled MFIs by incorporating the Simar and Wilson (2007) procedure of bootstrapping in the DEA model. The traditional DEA models do not account of the bias while in the calculation of efficiency estimates (Simar and Wilson, 2000), consequently, the results obtained in the second stage of analysis may mislead the authors. Therefore, we incorporated bootstrap procedure in the DEA model to assess the bias-corrected efficiency estimates. Further, the objectives of MFIs are to maximise the outputs by utilising the given level input resources. Therefore, the study has employed output-oriented constant returns to scale DEA model for the efficiency assessment. In addition, the study has compared the original efficiency scores of conventional DEA model with bias-adjusted efficiency estimates obtained using bootstrap DEA model. Moreover, the entire analysis is based on the bias-corrected efficiency estimates in the particular study.

4.1 Output-oriented CCR-based DEA model

The study used simple constant returns output-oriented DEA model to estimate the original efficiency scores (θ_k). Let's assume there are nMFIs (i.e., $j = 1, 2, \ldots, n$) where each MFI produces s output vector (y_{rj}) using m input vector (x_{ij}), then the efficiency of MFI "o" is calculated by solving the following linear programming:

$$\begin{aligned} &\max \theta_k = \phi + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \varepsilon \sum_{r=1}^{s} s_r^+\right) \\ &\text{s.t.} \ \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io}; \ \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \phi y_{ro} \\ &r = 1, 2, \ldots, s; i = 1, 2, \ldots, m; s_i^-, s_r^+ \geq 0; \lambda_j \geq 0; j = 1, 2, \ldots, n. \end{aligned} \tag{1}$$

Where θ_k represents the original efficiency estimate of the MFI "o" and ϕ represents the proportion by which MFI "o" can increase its outputs for a given level of inputs to become as efficient. The λ_j shows the share of MFI j in defining an efficient target for the MFI "o". The variables s_i^- and s_r^+ indicate input and output slack, respectively. The parameter ε is a non-Archimedean infinitesimal.

4.2 Bootstrap DEA procedure

The conventional DEA models do not have the statistical properties; therefore, may provide biased efficiency scores (Wijesiri *et al.*, 2015). To overcome this issue, we follow the concept of bootstrapping which repeatedly simulates the data generated process (DGP) to obtain the new estimates from each simulation (Efron, 1979; Efron and Tibshirani, 1993). The resampled estimates would mimic the distribution of original estimators (Simar and Wilson, 1998). In addition, the distribution of resampled estimates may be used to obtain the bootstrapped confidence intervals to confirm whether efficiency estimates are statistically significant or not (Fuentes, 2011). Notably, we follow the Simar and Wilson (2007) homogeneous bootstrapped procedure with 2,000 iterations to obtain the bias-adjusted efficiency estimates ($\widehat{\theta}_k^*$). For algorithm and more details on bootstrapping procedure, see Simar and Wilson (2007) and Bogetoft and Otto (2010).

4.3 Bootstrap truncated regression

After estimating the bias-corrected operational and financial efficiency scores, we employ the bootstrap truncated regression by following Simar and Wilson (2007) in order to identify the efficiency determinants. The other alternates, for example, ordinary least square (OLS) and tobit regressions and so on do not generate the valid estimates in the second stage of analysis (Simar and Wilson, 2007; Wijesiri *et al.*, 2015; Wijesiri *et al.*, 2017; Khan and Gulati, 2019). They argued that efficiency estimates obtained by the conventional DEA models are serially correlated; consequently, they provide the inconsistent estimates in the second stage of analysis. Therefore, we opted to employ double bootstrap truncated regression suggested by Simar and Wilson (2007). The study regresses the bias-corrected operational and financial efficiency estimates (i.e. obtained in the first stage of analysis) on the set of the selected environmental variables using the regression equation (2) as given as follows:

$$\widehat{\theta}_j^* = \alpha + \beta_1 E_j + \varepsilon_j \tag{2}$$

where $\widehat{\theta}_j^*$ is the bias-corrected efficiency score, α is the intercept, E is the raw vector of selected environmental variables, β is the estimated parameter and ε is error term. For more details on bootstrap truncated regression procedure, see Simar and Wilson (2007).

4.4 Data and inputs–outputs selection

4.4.1 Data. The study uses secondary data extracted from the MIX Market database (www.mixmarket.org) for the MFIs operating in ECA region during the year 2017–2018. The MFIs voluntarily report the audited financial statements and balance sheets to the MIX Market. It provides standardised and high-quality data of large number of MFIs operating globally (Servin *et al.*, 2012; Reichert, 2018). The data contain information on social and financial aspects of MFIs and have been used by a number of published studies (e.g. Servin *et al.*, 2012; Wijesiri *et al.*, 2017; Khan and Gulati, 2019, among others). At the time of data extraction, only 105 MFIs have reported to the MIX Market for the financial year 2017–2018. However, few MFIs were excluded in the analysis due to unavailability of data on selected variables. Finally, the present analysis is based on 67 MFIs which have complete information of the selected variables. The sample MFIs consist of different legal forms, that is, banks (12), credit unions (2), NBFIs (44), NGOs (6) and others (2). The data extracted for all the variables are in the US dollars. Further, in order to avoid the scaling issues, the study uses mean normalised data in the DEA model (see Widiarto and Emrouznejad, 2015; Widiarto *et al.*, 2017; Khan and Gulati, 2019, among others, who used this procedure in the MFIs' efficiency literature). We use the following equation to prepare the data to accommodate in the DEA model by following the Sarkis (2007) guidelines.

$$X_{\text{Norm}_{io}} = X_{io} \div \left[\left(\sum_{n=1}^{N} X_{in} \right) \Big/ N \right]$$

where X_{io} is the value for ith variable of MFI_o, N stands for total number of sampled MFIs and $X_{\text{Norm}_{io}}$ is the mean normalised value of ith variable of MFI_o.

4.4.2 Inputs–outputs selection. The most important and difficult task in the DEA procedure is to select the relevant inputs and outputs (Athanassopoulos, 1997; Sathye, 2003; Kumar and Gulati, 2014; Gulati, 2015; Arora *et al.*, 2018). The MFIs' empirical literature follows mainly two approaches: first, the *production approach* (see Benston, 1965) and second, *intermediation approach* (see Sealey and Lindley, 1997) as adopted from bank efficiency literature. The adoption of pure intermediation approach is not suitable for MFIs, since some MFIs are not allowed to take deposit which is a key input in intermediation approach (Gutiérrez-Nieto *et al.*, 2009). Further, the MFIs are considered to be mainly credit providers and not the deposit takers, so production approach is also not feasible to be adopted for all MFIs (Kumar and Sensarma, 2017). Therefore, neither of two approaches is perfect to adopt in case of bank industry (Berger and Humphrey, 1997; Kumar and Gulati, 2014; Gulati, 2015) or in the microfinance industry (Gutiérrez-Nieto *et al.*, 2009; Kumar and Sensarma, 2017; Fall *et al.*, 2018). Therefore, based on our specific objectives and the existing microfinance literature, the study opts for three different inputs: (1) total assets, (2) operating expenses and (3) interest expense on borrowings. In the outputs mix, the study chooses two outputs, namely (1) financial revenue and (2) net operating income. The definition and of input-output used in the DEA models and related study in the MFI empirical literature are reported in the Table 1. We design two DEA models to assess operational and financial efficiency estimates, specifications are given in Table 2. We follow the definitions of the entire selected variable as given by MIX Market data set. The descriptive statistics of chosen inputs and outputs are reported in Table 3. Total assets (*input*) defined as total of all asset accounts. Assets are the major inputs for the production in any institution and have been widely used in the microfinance efficiency literature (see Gutiérrez-Nieto *et al.*, 2009; Servin *et al.*, 2012; Piot-Lepetit and Nzongang, 2019, among others) and bank efficiency literature (see Staub *et al.*, 2019, among others). The operating expenses (*input*) consist of all expenses related to personnel expenses, administrative expenses and depreciation and amortisation expense, as explained by many authors, for example, Widiarto and Emrouznejad (2015); Lebovics *et al.* (2016); Widiarto *et al.* (2017); Wijesiri *et al.* (2017), among others. Operating expenses are the most important input in the production process which helps the loanable funds to be delivered to borrowers. Further, the MFI which incurred relatively lower operating expenses at given level of output is considered as relatively efficient. Interest expenses on borrowings (*input*) are the proxy of financial expenses, and it contains all the interest expenses incurred on short-term and long-term external borrowings. For the MFI which paid lower interest on borrowed funds at given level of output level, the DEA will reflects that MFI is relatively efficient. This is one of most used inputs in DEA framework in the MFIs' efficiency literature [Gutiérrez-Nieto *et al.*, 2007; Gutiérrez-Nieto *et al.*, 2009; Haq *et al.*, 2010; Servin *et al.*, 2012; Widiarto and Emrouznejad, 2015; Van Damme *et al.*, 2016; Widiarto *et al.*, 2017; Wijesiri *et al.*, 2017; Bibi *et al.*, 2018, Staub *et al.*, 2019 (bank efficiency literature), among others]. Financial revenue

Table 1.
Definition of input-output

Inputs	Initial	Definition	Usase in literatures	Unit
Total assets	TA	Total of all net assets	Wijesiri *et al.* (2015); Widiarto *et al.* (2017)	USD
Operating expenses	OE	It includes all expenses associated with personnel. depreciation and amortisation. and administration	Athanassopoulos (1997); Widiarto *et al.* (2017)	USD
Interest expense on borrowings	IE	Total of interest expenses 011 borrowed funds		USD
Outputs	**Initial**	**Definition**	**Usage in literatures**	**Unit**
Financial revenue	FR	Revenue collected from loan portfolio, interest and fee and from other financial assets	Widiarto and Emrouznejad (2015); Wijesiri *et al.* (2017); Khan and Gulati (2019)	USD
Net operating income	OI	Total revenue collected from loan portfolio only	Piot-Lepetit and Nzongaug, (2014)	USD

Note(s): Variable definitions have been taken from Mix Market, accessed in October, 2017 (https://www.themix.org/sites/default/files/publications/global_benchmark_report_fy2015_0.pdf)
Source(s): Authors' elaboration

Table 2.
DEA specifications

DEA (Mnemonic)	Model	Input variables	Output variables
TA. OE. IE – FR	Financial efficiency	Total assets (TA) Operating expenses (OE) Interest expense on borrowings (IE)	Financial revenue (FR)
TA. OE. IE – IO	Operational efficiency	Total assets (TA) Operating expenses (OE) Interest expense on borrowings (IE)	Net operating income (OI)

Source(s): Authors' elaboration

Table 3.
Descriptive statistics of input-output variables

Variable	Obs.	Mean	Min	Max	Std. Dev.
Total assets	67	1.43e+08	166939.80	2.58e+09	3.90e+08
Operating expenses	67	9,022,293	10073.47	8.33e+07	1.70e+07
Interest expense 011 borrowings	67	4,430,790	5044.9	5.29e+07	9,988,033
Financial revenue	67	2.49e+07	30122.45	3.34e+08	5.45e+07
Net operating income	67	3,162,931	1838.09	5.20e+07	7,390,307

Source(s): Authors' calculations

(*output*) includes all interest income from loans and other income from operations. The MFI which collects higher financial revenue at given level of inputs that will be declared as the financially efficient in the DEA model. This is the proxy of financial performance of the organisations (Gutiérrez-Nieto *et al.*, 2009; Widiarto and Emrouznejad, 2015; Wijesiri *et al.*, 2017; Khan and Gulati, 2019, among others). Net operating income (*output*) consists of all the income received from the operations after meeting all the operating expenses. This is the proxy of operational performance used in our study.

5. Empirical results

5.1 Estimation strategy

The study designs two separate DEA models (see Table 2) in order to estimate the financial and operational efficiency scores of individual MFIs operating in ECA region. In particular, we incorporate the bootstrap procedure suggested by Simar and Wilson (2000) in the DEA framework to measure the bias-adjusted efficiency scores in the first stage of analysis. Then, in order to identify the factors responsible for performance of MFIs, we regress the efficiency scores obtained in the first stage on the selected set of environmental variables by using bootstrap truncated regression using equation (2), following the Simar and Wilson (2007) guidelines.

5.2 Financial efficiency

The empirical results obtained in the first stage of analysis are reported in Table 4. In order to estimate the financial efficiency, we rely on efficiency scores of DEA model specified in Table 2. The kernel distribution pattern of original and bias-corrected efficiency scores is also reported in Figure 1. We note from the empirical results that mean of original financial efficiency scores is 0.673 and varies from a minimum of 0.397 to a maximum efficiency score of unity. However, we found that average of bias-corrected financial efficiency level of MFIs operating in the ECA region is 0.588 which is quite low. In another words, these MFIs are can enhance their financial performance by 41.20% without investing any additional input resources in the production process. In addition, we noted the minimum score of 0.344 and maximum efficiency score of 0.943. However, we did not find any major performance differences among the MFIs operating in the ECA region. It is worth mentioning here that almost the entire industry is operating at more or less same production frontier. Moreover, none of the MFIs have been found to be operating at the efficient frontier while estimating the bias-corrected efficiency envelop. However, while estimating the original efficiency envelope, we found that seven MFIs were operating at the best-practice frontier. In addition, most of the MFIs, that is, 73% have efficiency level between 40 and 80%. However, only ten MFIs were found to be attaining the efficiency level above 80%. Moreover, we found only five MFIs achieved the efficiency level above 80% in case of bias-corrected efficiency frontier. The results corroborate that there is enough space for the MFIs operating in the ECA region to increase the financial revenue by integrating more advance technology which would assist in reducing the transaction cost.

5.3 Operational efficiency

We measure the operational efficiency of individual MFIs operating in ECA region by following the DEA specification given in Table 2. The original (θ_k) and bias-corrected ($\widehat{\theta}_k^*$) operational efficiency scores are reported in Table 4 along with corresponding confidence intervals (CIs). We noted from empirical results that average original operational efficiency score is 0.573. This indicates that the ECA MFIs industry can increase the operational efficiency level by 42.70% without augmenting any input resources. Moreover, 36 out of 67 MFIs (i.e. 54%) have the efficiency level below 40%. In addition, we observed only 20 MFIs operating at 40–80% efficiency level. In contrast, only five MFIs have been found to be operating above 80% efficiency level. Further, we observed that five MFIs have been operating at best-practice frontier. While looking at the bias-corrected efficiency frontier, we noted that the average efficiency level is 0.496. which is slightly lower than original efficiency level. In addition, we observed that only one MFI is operating above 80% efficiency level. Moreover, the results revealed that 46 out of 67 (i.e. 68.66%) MFIs operating below 40% efficiency level. Further, we found that none of the MFIs is operating at the best-practice

MFI codes	Financial efficiency θ_k	Bias	$\hat{\theta}_k^*$	95% CI LB	UB	Operational efficiency θ_k	Bias	$\hat{\theta}_k^*$	95% CI LB	UB
MFI01	0.619	0.114	0.506	0.375	0.611	0.365	0.056	0.309	0.047	0.453
MFI02	0.737	0.083	0.654	0.526	0.728	0.816	0.123	0.694	0.503	0.805
MFI03	0.504	0.044	0.460	0.409	0.496	0.398	0.033	0.365	0.115	0.492
MFI04	0.550	0.143	0.407	0.207	0.541	0.922	0.299	0.623	0.108	0.899
MFI05	0.820	0.089	0.730	0.618	0.804	1.000	0.471	0.529	0.015	0.919
MFI06	0.642	0.033	0.609	0.571	0.635	0.336	0.007	0.329	0.019	0.434
MFI07	0.545	0.030	0.514	0.472	0.539	0.553	0.145	0.408	0.240	0.520
MFI08	0.758	0.047	0.711	0.639	0.753	0.632	0.108	0.524	0.365	0.620
MFI09	0.549	0.028	0.521	0.485	0.543	0.350	0.087	0.263	0.162	0.330
MFI10	0.735	0.064	0.671	0.595	0.724	0.835	0.133	0.702	0.502	0.813
MFI11	0.778	0.050	0.728	0.660	0.769	0.399	0.039	0.360	0.107	0.593
MFI12	0.949	0.143	0.806	0.667	0.932	0.623	0.177	0.446	0.229	0.593
MFI13	1.000	0.230	0.770	0.586	0.971	0.805	0.131	0.674	0.461	0.787
MFI14	0.448	0.038	0.410	0.363	0.442	0.367	0.019	0.345	0.026	0.563
MFI15	0.447	0.032	0.415	0.370	0.443	0.390	0.046	0.344	0.089	0.585
MFI16	0.690	0.045	0.645	0.577	0.683	0.344	0.058	0.286	0.200	0.337
MFI17	0.514	0.033	0.481	0.443	0.508	0.394	0.025	0.369	0.037	0.688
MFI18	0.594	0.033	0.561	0.525	0.587	0.446	0.082	0.364	0.250	0.432
MFI19	0.636	0.032	0.604	0.562	0.630	0.208	0.042	0.166	0.109	0.201
MFI20	0.681	0.037	0.645	0.602	0.674	0.386	0.018	0.368	0.124	0.478
MFI21	0.662	0.042	0.620	0.573	0.653	0.531	0.095	0.437	0.301	0.513
MFI22	0.674	0.074	0.601	0.475	0.669	0.348	0.051	0.297	0.217	0.344
MFI23	0.864	0.111	0.753	0.582	0.855	0.363	0.009	0.354	0.039	0.562
MFI24	0.835	0.048	0.787	0.736	0.823	1.000	0.259	0.741	0.443	0.942
MFI25	0.786	0.084	0.701	0.576	0.774	0.584	0.230	0.354	0.032	0.566
MFI26	0.531	0.088	0.443	0.348	0.521	0.464	0.075	0.388	0.279	0.452
MFI27	1.000	0.219	0.781	0.535	0.981	0.214	0.031	0.183	0.132	0.211
MFI28	0.708	0.037	0.671	0.627	0.702	0.649	0.172	0.477	0.277	0.618
MFI29	0.504	0.068	0.436	0.359	0.494	0.350	0.103	0.247	0.106	0.340
MFI30	0.625	0.049	0.576	0.510	0.616	0.142	0.025	0.117	0.082	0.137
MFI31	0.532	0.030	0.502	0.470	0.525	0.158	0.033	0.125	0.081	0.152
MFI32	0.510	0.043	0.467	0.415	0.501	0.320	0.094	0.225	0.110	0.300
MFI33	0.687	0.043	0.644	0.596	0.678	0.282	0.069	0.213	0.127	0.266
MFI34	0.490	0.066	0.423	0.344	0.480	0.083	0.018	0.064	0.039	0.081
MFI35	0.720	0.091	0.629	0.482	0.712	0.600	0.086	0.514	0.378	0.594
MFI36	0.484	0.032	0.453	0.411	0.479	0.201	0.038	0.163	0.110	0.195
MFI37	0.833	0.147	0.686	0.517	0.819	0.454	0.147	0.308	0.138	0.422
MFI38	0.532	0.042	0.490	0.439	0.524	0.448	0.119	0.329	0.177	0.422
MFI39	0.508	0.086	0.421	0.325	0.498	0.361	0.024	0.323	0.003	0.759
MFI40	0.397	0.052	0.344	0.288	0.388	0.233	0.013	0.210	0.139	0.228
MFI41	0.794	0.072	0.721	0.632	0.784	0.479	0.168	0.311	0.127	0.442
MFI42	0.473	0.037	0.436	0.384	0.467	0.391	0.074	0.317	0.126	0.281
MFI43	0.667	0.033	0.634	0.593	0.661	0.321	0.047	0.274	0.112	0.213
MFI44	0.823	0.047	0.775	0.716	0.815	1.000	0.196	0.804	0.550	0.957
MFI45	0.457	0.055	0.402	0.342	0.449	0.282	0.066	0.216	0.128	0.274
MFI46	0.507	0.059	0.448	0.387	0.497	0.302	0.049	0.253	0.178	0.294
MFI47	0.436	0.034	0.402	0.360	0.430	0.282	0.077	0.205	0.111	0.267
MFI48	0.883	0.150	0.733	0.496	0.878	0.772	0.108	0.664	0.487	0.766
MFI49	1.000	0.096	0.904	0.783	0.984	0.424	0.144	0.280	0.105	0.406
MFI50	1.000	0.190	0.810	0.630	0.980	0.897	0.372	0.525	0.022	0.859
MFI51	0.420	0.040	0.380	0.318	0.414	0.338	0.012	0.376	0.011	0.133
MFI52	0.555	0.090	0.465	0.344	0.546	0.336	0.123	0.213	0.018	0.326

(*continued*)

Table 4.
Original, BIAS, and bias-corrected financial and operational efficiency scores

MFI codes	Financial efficiency θ_k	Bias	$\widehat{\theta}_k^*$	95% CI LB	UB	Operational efficiency θ_k	Bias	$\widehat{\theta}_k^*$	95% CI LB	UB
MFI53	0.826	0.143	0.683	0.465	0.812	0.465	0.159	0.306	0.039	0.450
MFI54	0.450	0.058	0.392	0.324	0.442	0.256	0.111	0.145	0.009	0.243
MFI55	0.437	0.034	0.403	0.353	0.431	0.238	0.087	0.152	0.048	0.224
MFI56	1.000	0.556	0.444	0.291	0.975	0.700	0.211	0.489	0.096	0.688
MFI57	0.457	0.029	0.428	0.391	0.451	0.289	0.073	0.216	0.122	0.275
MFI58	1.000	0.289	0.711	0.430	0.982	0.486	0.169	0.317	0.123	0.459
MFI59	0.782	0.098	0.684	0.574	0.768	1.000	0.347	0.653	0.284	0.909
MFI60	0.633	0.031	0.602	0.563	0.628	0.328	0.050	0.278	0.113	0.218
MFI61	1.000	0.057	0.943	0.875	0.988	1.000	0.344	0.656	0.321	0.901
MFI62	0.660	0.100	0.560	0.449	0.644	0.447	0.103	0.344	0.200	0.437
MFI63	0.678	0.133	0.545	0.373	0.672	0.714	0.102	0.612	0.446	0.707
MFI64	0.778	0.092	0.686	0.575	0.768	1.000	0.399	0.601	0.207	0.898
MFI65	0.467	0.045	0.422	0.355	0.460	0.324	0.013	0.311	0.009	0.214
MFI66	0.894	0.059	0.836	0.759	0.882	0.585	0.156	0.429	0.227	0.552
MFI67	0.929	0.216	0.713	0.421	0.920	0.371	0.020	0.351	0.072	0.291
Average	0.673	–	0.588	–	–	0.573	–	0.496	–	–
No. of efficient MFIs	7	–	0	–	–	6	–	0	–	–
0 ≤ Eff. ≤ 0.40	1	_	3	_	_	36	–	46	–	–
0.40 ≤ Eff. ≤ 0.80	49	_	59	_	_	20	–	20	–	–
0.80 < Eff. < 1	10	_	5	_	_	5	–	1	–	–

Source(s): Authors' calculations

Table 4.

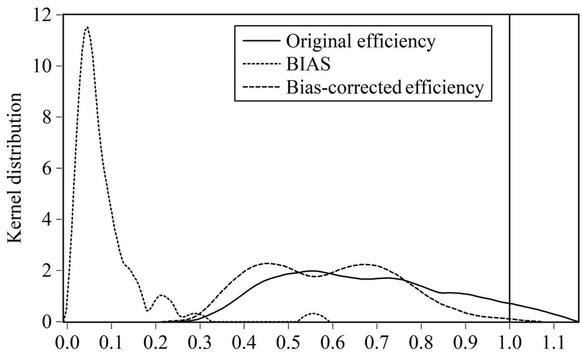

Figure 1.
Kernel distribution of financial efficiency model

frontier while looking at the bias-adjusted efficiency frontier. In addition, the kernel distribution of operational efficiency scores demonstrate that MFIs' performances are equally distributed, no major performance differences have been found among MFIs on the operational efficiency frontier. The entire ECA MFIs industry has lots of scope to enhance the operational efficiency level by incorporating advanced technology in the production process (see Figure 2).

Further, we compare the financial and operational efficiency levels of MFIs operating in the ECA region. We observed that MFIs were found to be performing relatively higher in terms of financial efficiency than operational efficiency (see Figure 3). There are only few MFIs which are performing better in dual aspects: financial and operational. However, the entire ECA region has MFIs with lower operational efficiency level (see Figure 3) and higher level of bias has been reported in case of operational efficiency frontier.

5.4 Drivers of efficiency – bootstrap truncated regression

We extend our analysis to identify the drivers of financial and operational efficiency of MFIs operating in the ECA region. The study employs the bootstrap truncated regression (Simar and Wilson, 2007) to determine the possible factors affecting the financial and operational efficiency. We design two separate models to capture the explanatory variables following equation (2). Table 5 demonstrates the variables and their definitions incorporated in the models. The larger MFIs (i.e. in terms of assets or loan portfolio) may get economies of scope as well as scale benefits in providing the financial services and become relatively efficient (Hermes and Hudon, 2018). Therefore, to capture the scale and scope effects on the financial and operational efficiency, we have incorporated the log of assets (*SIZE)* as a proxy of size of MFIs. The literature provides heterogeneous results on association between financial performance and credit quality (Daher and Le Saout, 2015). Therefore, the study has taken the portfolio at risk (30 days) – *PAR30* as a proxy for credit quality of loan portfolio of individual MFI in order to examine the impact of credit quality of financial and operational performance of MFIs. This has been used widely in the MFIs' efficiency literature (see Bibi *et al.*, 2018; Khan and Gulati, 2019). In addition, debt-to-equity ratio indicates how much the MFI's worth is

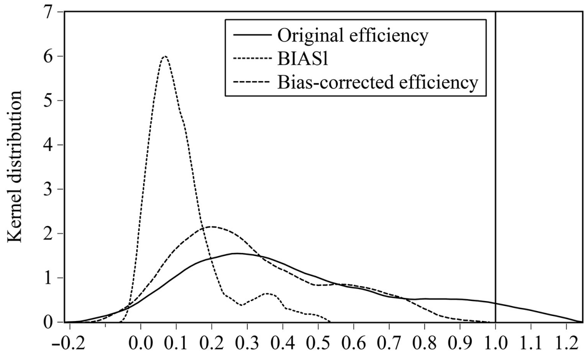

Figure 2.
Kernel distribution of operational efficiency model

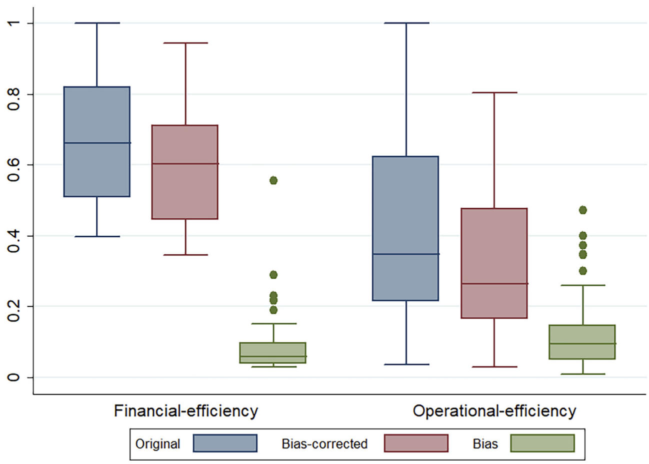

Figure 3.
Boxplot-financial and operational efficiency scores

funded by external borrowings (Ngo *et al.*, 2014). We have taken the debt-to-equity ratio (*DER*) as a proxy of liquidity of MFIs. The orientation of MFIs for-profit matters a lot in determining the level of performance (Khan and Gulati, 2019). In addition, for-profit MFIs are considered to be inclined towards more profitable clients and earn relatively more revenue by placing larger size of loan (Khan and Gulati, 2019). However, not-for-profit MFIs also generate sufficient revenue to sustain in the long run. Therefore, to capture the impact of profit status, we have used the dummy for profit status (see Table 5). In addition, the size of board has been found to have both positive and negative impact on MFIs' performance (Bohren and Strom, 2010). To scrutinise the association between the corporate governance and MFIs' performance, the study has used the board size (*BOARD*) in the model, to examine the possible association with financial and operational performance of MFIs in the ECA region.

The study regresses the bias-adjusted financial and operational efficiency scores (i.e. obtained in the first of analysis) on the set of selected environmental variables using equation (2). The results of bootstrap truncated regression are reported in Table 6. We note from the empirical results that the MFIs are getting economies of scale benefits. This is evident from the empirical results, we noted that the association of assets size with financial and operational efficiency is positive and statistical significant. Our results are also corroborated the findings of Cull *et al.* (2007), Caudill *et al.* (2009), Ngo *et al.* (2014), Gohar and Batool (2015), and Khan and Gulati (2019) in the literature. In addition, we observed that the bad credit quality (*PAR30*) deteriorates the financial and operational efficiency of MFIs. These findings are statistically significant at 5% level significance. The similar findings have been observed by Huq *et al.* (2017) and Chikalipah (2018). Further, we noted from our results that the debt fund (borrowed capital) has earned the financial revenue by placing the credit to the borrower. However, the financial expenses on external borrowings decrease the operational efficiency of MFIs. This has been observed from the positive relationship with financial performance and negative and statistically significant association of debt–equity ratio with operational performance. Moreover, for-profit MFIs have been found to have higher financial and operational efficiency. For-profit MFIs tend to serve better off clients in order to reduce the cost per transaction (Ngo *et al.*, 2014). This has been evident from the positive and statistically significant association between profit status and financial and operational efficiency of MFIs. Similar observations have been noted by Khan and Gulati (2019). Further, we found from the results that the size of the board has positive and statistically significant association with both financial and operational efficiency of MFIs' operation in the ECA region. However, larger board size may also deteriorate the performance due to higher cost of salary and delays in decision-makings (Bohren and Strom, 2010). In addition, Gohar and Batool (2015) also found the negative association between board size and performance of Pakistani MFIs.

Predictor	Symbol	Description	Expected sign
(i) Size (assets)	*SIZE*	Log of total assets	+
(ii) Portfolio at risk (30 days)	*PAR30*	The fraction of gross load portfolio remains due for more than 30 days	−
(iii) Debt to equity ratio	*DER*	Debt divided by equity capital	−
(iv) Profit statics	*PROFIT*	Dummy: for profit = 1, not for profit = 0	+
(v) Size of board	*BOARD*	Number of board members	±

Source(s): Authors' elaboration

Table 5. Description and expected sign of the predictors

Explanatory variables	Financial efficiency	Operational efficiency
Constant	0.431 (0.064)***	0.163 (0.127)
SIZE	0.328 (0.012)***	0.314(0.024)**
PAR30	−0.200 (0.243)**	−0.932 (0.637)**
DER	0.188 (0.008)	−0.138 (0.017)**
PROFIT	0.133 (0.041)***	0.225 (0.090)**
BOARD	0.310(0.011)*	0.226 (0.020)*
Number of observation	52	52
Wald χ^2 (p-value)	16.70 (0.002)	9.57 (0.048)
Sigma	0.013 (0.013)***	0.201(0.127)

Note(s): 1. Figures in parentheses are bootstrapped standard error
2. ***, ** and * indicate coefficients are significant at 1, 5 and 10% levels, respectively
3. Number of iteration used = 2000 following the Simar and Wilson (2000) guidelines
Source(s): Authors' calculations

Table 6. Results of bootstrap truncated regression

6. Discussion

The findings from the empirical results indicate that the MFIs operating in the ECA region are relatively more financially efficient than operationally. Though there is lots of scope available for further improvement in the performance in terms of both the aspects. In particular, the reported efficiency estimates are bias-adjusted which reflects the true image of MFIs operating in the ECA nations. Among all the regions, the productivity of the ECA region is very low in terms of borrowers per staff member. This could have triggered the operational expenses of MFIs to be high, consequently, the MFIs become operationally inefficient. Besides, the study observes that the repayment rate is relatively low among the ECA MFIs. This reflects that the risk management units of MFIs are not able to identify the defaulters in advance before approval of the credit. Moreover, Peek and Rosengren (2005) observed the negative association between risk management practices and loan portfolio. In particular, the stringent policies for loan approval may positively affect the loan performance repayments. The deteriorate credit quality negatively impacted the financial revenue of MFIs, subsequently, the liquidity issue may arise which could harm the financial and operational performance of MFIs.

We noted that large number of employees/staff members in the MFIs incurred high operating expenses which are not contributing the extra marginal revenue in the system. Therefore, unproductive/less productive staff of MFIs has created the fixed burden of salaries and other expense on the MFIs. To enhance the efficiency and productivity of the MFIs' operations, the leaders need to adopt the latest technology available to process the transaction and bring the cost per borrower. We observed that the cost of serving the borrowers (i.e. US$198.10 per borrower) is very high in entire ECA region compared to other regions. For instance, South Asian MFIs are the most cost-effective in the world which have cost per borrower of US$32.70 only. The MFIs are advised to implement artificial intelligence (AI) and other state-of-the-art technology to process the credit applications to bring the cost per dollar lent down. Further, the deposit mobilisation is relatively low in the region, in order to save the financing cost of loanable funds; the MFIs need to induce more and more depositors in the microfinance stream.

Besides, our results confirm that larger the MFIs, assets base is positively associated with the performance of MFIs. This indicates that MFIs are getting the economies of scale. The similar findings have been noted by Caudill *et al.* (2009) in case of ECA and Indian MFIs, respectively. The large MFIs enjoy even the lower interest rates for their borrowings, and as a result, their performance gets improved. Further, we found that the repayment rate is low relatively in the entire ECA region. Moreover, in case of banks, the portfolio at risk for 30 days is the highest at 18.80%, which negatively impacted the financial and operational performance. Our findings are corroborated by Huq *et al.* (2017) and Chikalipah (2018) in case of South Asia and sub-Saharan African MFIs, respectively. Moreover, the results reflect that if the MFIs have the information about risky area, then they have the courage to augment the loan repayment rates. The MFIs have prior chance to disqualify the loan application and get rid from defaulters in advance. Therefore, the MFIs must have risk assessment units which should closely work with loan officers' team. Further, we observed that the larger board size may delay the decision-making process and create extra burden of high payout and other expenses, consequently, the performance of MFIs gets hampered. Similar conclusions have been drawn by Gohar and Batool (2015) by analysing the performance of Pakistani MFIs. Further, we noted from the empirical results that for-profit MFIs outperform in terms of both the aspects: financial and operational efficiency. This reflects that banks and other NBFI types of MFIs, for example, for-profit institutions appear to be more appropriate while targeting to endorse the expansion of microfinance in the ECA.

7. Conclusions and managerial implications

The present study attempts to benchmark the financial and operational performances of MFIs operating in ECA region during the financial year 2017–2018. In addition, the study also identifies the performance drivers of MFIs which particularly affect the financial and operational efficiency estimates of MFIs. In a nut shell, the study has obtained the bias-corrected financial and operational efficiency estimates of individual MFIs in the first stage of analysis by incorporating the bootstrap procedure in the DEA model as suggested by Simar and Wilson (1998, 2000). Then in the second stage of analysis, in order to identify the performance drivers, the study regressed the efficiency scores (i.e. obtained in the first stage of analysis) on the selected set of environmental variables by applying the bootstrap truncated regression model (see equation 2) following the Simar and Wilson (2007) guidelines.

We note from the empirical results that financial efficiency is higher than operational efficiency of MFIs operating in the ECA region. This indicates that the MFIs are generating enough financial revenue (however, not sufficient to become fully efficient); however, these MFIs are not managing their operations efficiently. Further, the cost of per dollar lent is relatively higher in case of MFIs operating in the ECA region. In addition, no single MFI has been found to be operating on the best-practice frontier in terms of both financial and operational bias-adjusted efficiency envelops. Moreover, in terms of original efficiency estimates, we note seven and five MFIs were found to be efficient in respect of financial and operational efficiency, respectively. In addition, most of the MFIs, that is, 73% of the sample MFIs report the performance level below 80%. However, only ten MFIs were found to be attaining the efficiency level above 80% in terms of financial aspect. In contrast, in terms of operational efficiency, only five MFIs have been found to be operating above 80% efficiency level. In addition, 46 out of 67 sampled MFIs were found to be operating below 40% efficiency level. Moreover, only one MFI has achieved the efficiency level above 80%.

Further, the study observed that corporate governance, that is, board size has positive and statistically significant impact on MFIs' performance in the ECA region. The study also confirms that the MFIs are getting economies of scale, the larger asset size of MFIs assists in achieving the higher efficiency level. Further, if the credit quality decreases, the efficiency level is prone to decline significantly. The bad credit quality deteriorates both financial revenue and operational efficiency. Further, we note that the orientation of MFIs for-profit or not-for-profit matters a lot in determining both financial and operational efficiency. The managers of for-profit MFIs use state-of-the-art practices for revenue collection and minimise the operational cost so that their efficiency in terms of profit can be enhanced with the given level of resources. Moreover, we observe from the results that the presence of high-level borrowed capital in the loanable funds enhances the financial efficiency in terms of revenue collection. However, the operational efficiency decreases due to financial expenses incurred on the external borrowed capital.

The present study provides the robust efficiency estimates and factors responsible to determine the financial and operational efficiency of MFIs operating in the ECA region. The study offers reliable and up-to-date policy conclusions which can be used by interested stakeholders of microfinance in the ECA. Further, in order to achieve higher efficiency level, the managers of inefficient MFIs may redesign their operating practices by following the strategies of relatively efficient peers in the MFIs industry. The MFIs need to integrate the advanced technology to bring the transaction cost down to become cost-efficient. To improve the credit quality of loan portfolio, there must be well-designed framework to assess the "*capacity to pay*", "*intention to pay*" and "*propensity to pay*" of the prospected borrowers before lending to them. In addition, managers need to decide the optimum level of leverage to maximise the revenue out of external funds. Moreover, the adequate number of qualified and expert board members must be hired in order to drive the entire operation in the right direction so that the MFIs may offer maximum benefits to all the stakeholders of microfinance.

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