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PII: S1042-4431(17)30617-0
DOI: https://doi.org/10.1016/j.intfin.2017.12.008
Reference: INTFIN 1008

To appear in: *Journal of International Financial Markets, Institutions & Money*

Received Date: 9 August 2016
Accepted Date: 30 December 2017

Please cite this article as: U. Bibi, H. Ozer Balli, C.D. Matthews, D.W.L. Tripe, Impact of gender and governance on microfinance efficiency, *Journal of International Financial Markets, Institutions & Money* (2017), doi: https://doi.org/10.1016/j.intfin.2017.12.008

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Abstract:

This study examines the efficiency of South Asian microfinance institutions (MFIs) using Data Envelopment Analysis. Bias corrected efficiency estimates for the individual MFIs are regressed on a set of explanatory variables (including governance and gender) employing the double bootstrap truncated regression approach (Simar & Wilson, 2007) and panel data regression. First stage results suggest that South Asian MFIs are more financially efficient than socially efficient. More precisely, we find that these MFIs are technically inefficient but scale efficient, and that there was some improvement in financial efficiency over time. The relatively low average efficiency scores show that there is quite a bit of variation in microfinance efficiency. Second stage regression reveals that female loan officers are positive determinants of MFIs' efficiency. We find a strong association between a MFI's governance and its financial and social efficiency.

JEL codes:
D24, G21, G 34

Acknowledgements:
David Tripe acknowledges the support of the Czech Science Foundation (Project No GA 17-02509S).

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Abstract:

This study examines the efficiency of South Asian microfinance institutions (MFIs) using Data Envelopment Analysis. Bias corrected efficiency estimates for the individual MFIs are regressed on a set of explanatory variables (including governance and gender) employing the double bootstrap truncated regression approach (Simar & Wilson, 2007) and panel data regression. First stage results suggest that South Asian MFIs are more financially efficient than socially efficient. More precisely, we find that these MFIs are technically inefficient but scale efficient, and that there was some improvement in financial efficiency over time. The relatively low average efficiency scores show that there is quite a bit of variation in microfinance efficiency. Second stage regression reveals that female loan officers are positive determinants of MFIs' efficiency. We find a strong association between a MFI's governance and its financial and social efficiency.

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1. Introduction

Microfinance Institutions (MFIs) are a special type of financial institution that resemble conventional banks in collecting money (accepting deposits) and making loans (Gutierrez-Goiria, San-Jose, & Retolaza, 2017). The difference is the target market, as MFIs lend small amounts to the poor, accept grants and generally have lower default rates than conventional banks (Haq, Skully, & Pathan, 2010). Moreover, MFIs are important institutions in financial systems in developing countries, especially South Asia[1] – where the concept was first introduced – but they also play a significant role in social and economic development of the region. To ensure that their role in economic development can be sustained, their financial and social performance needs to be assessed (Sainz-Fernandez, Torre-Olmo, López-Gutiérrez, & Sanfilippo-Azofra, 2015). This can cement MFIs' roles in South Asia's economic development and future policy making. This paper aims to examine the efficiency of South Asian MFIs and determine the influence of governance mechanisms and the presence of females in different roles on efficiency of MFIs.

Over the past few decades there has been a lot of research on efficiency in banking and as microfinance resembles small scale banking, techniques for performance studies that have been common in banking research are being applied to microfinance (Mersland & Strøm, 2009). The efficiency of MFIs has attracted relatively less research attention but this scarcity of literature (Gutierrez-Nieto, Serrano-Cinca, & Molinero, 2007; 2009; Hermes, Lensink, & Meesters, 2011; Piot-Lepetit & Nzongang, 2014; Wijesiri, Viganò, & Meoli, 2015) gives the opportunity to further explore the efficiency determinants of these institutions.

In the present paper we use a standard non-parametric approach – DEA – that prevails in the banking literature to measure the social and financial performance of MFIs. An innovative aspect of this paper is the methodological approach. In the first stage of our analysis, we use the slacks-based measure (SBM)-super efficiency model (to identify outliers in our database) and then the DEA bootstrap approach. In the second stage, we use truncated bootstrapped regressions to analyse the sampled MFIs' specific operating characteristics that may impact

[1] The focus on South Asia gives us a relatively larger pool of relatively similar MFIs than we would have obtained from looking at just one country (although our data set is dominated by India and Bangladesh). On the other hand, microfinance in South Asia is characterised by a significantly smaller average loan size (and more rural lending and lending to women) than is seen in some other microfinance markets (particularly Latin America), which means that results for studies focusing on South Asia may differ from those obtained from global studies.

on variations in microfinance efficiency. Our research will add to existing literature in the following ways. First, very little of the prior research has made use of the double bootstrap: one exception is Wijesiri et al. (2015), but they studied only one country (Sri Lanka) for one year. We look at the countries of South Asia over a longer time period. Secondly, we also extend use of the bootstrapped efficiency scores by exploring the impacts of governance and the role of women.

Corporate governance and gender variables have been identified as a key bottleneck in strengthening MFIs' financial sustainability (financial performance) and increasing their outreach (social impact) (Beisland, Mersland, & Strøm, 2015). Microfinance raises the need for an appropriate governance structure as there have been recurring examples of poor governance. For example, the 2010 problems in Andhra Pradesh[2], India, not only affected the MFIs' performance but also negatively affected the overall Indian economy, ultimately increasing poverty (Taylor, 2011).

Moreover, microfinance is particularly suited for studying the effect of female involvement because of its social mission, its diverse institutional conditions and entrepreneurial nature (Aggarwal, Goodell, & Selleck, 2015; Civitarese & Leite, 2017). There are a handful of studies which find mixed results in terms of identifying the role of gender and corporate governance on efficiency of MFIs. For example, Armendariz & Morduch (2010) argue that female targeting has often been attributed to increased efficiency within microfinance. D'Espallier, Guérin, & Mersland (2011) confirm that the targeting of women leads to higher repayment rates in MFIs. Boehe & Cruz (2013) using data of 26 microfinance projects in 22 African, Eastern European, Latin American, and Asian countries found that female membership in MFIs improves the MFI's performance through enhanced debt repayment.

Strøm, D'Espallier, & Mersland (2014) investigate the role of female leadership on MFIs' governance and financial performance in a global panel of 329 MFIs in 73 countries covering the years 1998–2008. They find female leadership to be significantly associated with younger firms, larger boards, and more female clientele. They also find that having female board

[2] In Andhra Pradesh, India, in the first nine months of 2010, more than 200 microfinance clients committed suicide due to excessive debt claims and aggressive loan collection, a problem that has been blamed on poor governance, among other factors.

members is positively related to MFI performance, but this is not a result of improved governance. Similarly, Mersland & Strøm (2009) find that the MFIs with female CEOs achieve stronger financial performance due to their better understanding of the market in which the MFI operates. This implies that a MFI where the market is matched with leadership with the same traits (referring here to gender) performs better. Galema, Lensink, & Mersland (2012)
examine the impact of CEO power on risk taking of MFIs and find that CEOs of microfinance non-governmental organisations (NGOs) have more decision-making freedom than other types of MFIs. This induces them to make more extreme decisions that increase risk.

Beck, Behr, & Madestam (2018) and Marrit, Lensink, & Servin (2015) both look at the role of women loan officers and their impact on repayment rates. Beck et al. (2018) look at a MFI in Albania, and obtain some confirmation of their results with a sample from Bolivia. They find that female loan officers show lower arrears than their male counterparts, with a stronger effect found for female borrowers, a finding which they attribute to female loan officers' stronger empathy. By contrast, in a Mexican MFI, Marrit et al. (2015) find that male officers perform better.

D'Espallier, Guerin & Mersland (2013) find that a focus on women in MFIs is significantly related to international orientation, collective lending methods, smaller loans and a non-commercial status. The smaller loans led to higher operating costs. They confirm that lending to women is associated with lower loan losses, although the gender mix of clients had no other impact on performance in their study. They caution, however, that their results are obtained from a global analysis and that there would be benefit in studying the relationships in various regions and cultural settings. This provides a rationale for our study to focus on South Asia.

Prior research has given us a glimpse of different aspects of analysis of governance and gender determinants on efficiency of MFIs. The novelty of our research is that we have combined both gender and corporate governance indicators to analyse this link. We address the following research questions in this paper. Firstly, how efficient are MFIs' operations in South Asian countries, and what factors explain the variation in microfinance efficiency?

Second, as suggested by Strøm et al. (2014), could governance and the involvement of women be key determinants of MFIs' efficiency?

The governance mechanisms under consideration in this study are categorised as internal and external governance (Caudill, Gropper, & Hartarska, 2009). Internal mechanisms generally include ownership of a MFI, board composition and regulatory structures while external mechanisms include political stability and the control of corruption. The ownership structures of MFIs are categorised as non-profit-oriented and profit-oriented[3]. We expect that profit-oriented MFIs should concentrate more on financial efficiency, and non-profit-oriented MFIs more on social efficiency. Among external governance variables, institutional quality can either aggravate or lessen uncertainties that arise from incomplete information by channelling information about market conditions, reduce risk related to property rights, and make politicians accountable to citizens (Bora et al., 2004). Thus, we expect internal and external governance to be positive efficiency determinants for MFIs. Along with governance variables, we use some gender variables – percentage of female board members (PFMs), percentage of female loan officers (PFOs), and percentage of female borrowers (PFBs) – in our regressions to study the overall impact of females on MFI efficiency. Many MFIs deal mainly with women so we expect that females on boards, as officers and as clients will positively impact the financial and social efficiency level of MFIs.

The rest of the paper is organized as follows. In section 2 we discuss the methodology that includes DEA models and regression models. Section 3 introduces the data and variables selected for empirical analysis. Section 4 describes the DEA results and regression results. Section 5 concludes.

2. Methodology

In the first-stage of the analysis, we use an input-oriented model for financial efficiency and an output-oriented model for social efficiency. An input-oriented model assumes a proportional reduction in input usage with output level held constant, while an output-oriented model assumes a proportional increase in output production with input levels held

[3] The non-profit-oriented MFIs such as NGOs and credit unions are mainly built on social objectives of serving the poor, while profit-oriented MFIs such as microfinance banks are working to serve both outreach and financial sustainability objectives.

fixed. Marakkath (2014) has argued that output orientation is not appropriate for microfinance as maximization of outputs, like interest rates and profit margins, may amount to client exploitation. However, as we use the number of active borrowers as an output for social efficiency, use of an output orientation to maximise social performance relative to input resources is considered more appropriate.

We present the input oriented model using variable returns to scale (VRS) assumptions in Equation 1 and the output oriented model in Equation 2[4].

Input-Oriented Model

$$\min_{\theta,\ \lambda_j} \ \theta \qquad \text{(Equation 1)}$$

Subject to:

$\sum_{j=1}^{n} \lambda_j Y_{rj} \geq Y_{rj}$ (Y is output, r = 1,...,s)

$\theta X_{ij} \geq \sum_{j=1}^{n} \lambda_j X_{ij}$ (X is input, i = 1,...,m)

$\sum_{j=1}^{n} \lambda_j = 1$ (MFIs, j = 1,...,n)

$\lambda_j \geq 0$

Output-Oriented Model

$$\max_{\theta,\ \lambda_j} \theta \qquad \text{(Equation 2)}$$

Subject to:

$\theta Y_j + \lambda_j Y_{rj} \geq 0$ (Y is output, r = 1,...,s)

$X_i - \lambda_j X_{ij} \geq 0,$ (X is input, i = 1,...,m)

$\sum_{j=1}^{n} \lambda_j = 1$ (MFIs, j = 1,...,n)

$\lambda_j \geq 0$

The input-oriented model attempts to proportionally reduce inputs of the MFIs as much as possible while not decreasing its current level of outputs. This process is applied for each MFI, and an optimal solution of θ yields an efficiency score for a MFI where $\theta = 1$ indicates an efficient MFI and $\theta < 1$ an inefficient MFI. $\sum_{j=1}^{n} \lambda_j = 1$, establishes the model as VRS. The output-oriented DEA model is very similar to input-oriented DEA models, with θ defining technical efficiency (TE) scores that vary between zero and one.

The DEA surface differs depending on the scale assumptions i.e. CRS (constant returns to scale, also referred to as CCR) or VRS (also referred to as BCC). If returns to scale are assumed to be constant, the appropriate model is CRS; otherwise, VRS is preferable. In the present study, due to the variety in size of the institutions, the constant returns to scale assumption may not apply, leading us to choose the VRS model. Overall TE is measured by using input-oriented or output-oriented directions of both the CRS and VRS models with any difference reflecting scale inefficiency. Scale efficiency (SE) is calculated as follows:

[4] For more detail on DEA, see Coelli et al. ((2005).

$SE = \theta_{jCRS} / \theta_{jVRS}$ (θ_j represents TE scores of each MFI) (Equation 3)

A number of different ways have been suggested in the microfinance literature to select input and output variables. These efficiency techniques are ranked under different sets of input and output variables that are mainly based on intermediation and production models used in banking research (Berger & Humphrey, 1997). Mindful of the guidance[5] offered by Dyson et al. (2001, pp. 247-250) in choosing particular sets of input and output variables, we would argue that these are not strictly applicable to the operating objectives of MFIs. As most MFIs do not collect deposits (only regulated MFIs collect deposits) and since one of the conditions of DEA methodology is to choose homogenous decision making units (DMUs) for the sample, deposit-taking activities are excluded from our analysis (for more detail see Gutierrez-Nieto et al., 2007).

The inputs and outputs in the model are selected based on the outreach and sustainability approaches suggested by Gutierrez-Nieto et al. (2017) For social efficiency, three input variables (number of personnel, operating expenses and financial expenses) and two output variables (number of active borrowers[6] and gross loan portfolios) are selected, with financial revenues replacing number of active borrowers as an output variable for financial efficiency.

We also employ a slacks-based super-efficiency measure (super-SBM) model[7] (Tone, (2002) to identify outliers in our data set. Efficient units have super-efficiency values greater than or equal to one and there seems to be some agreement (although no 'cut-off' standard exists) that values above 2.0 indicate DMUs as outliers (Hartman, Storbeck, & Byrnes, 2001).

After estimating DEA efficiency scores (bounded at 0 and 1), using a bootstrap as per Simar & Wilson (2007) in the first-stage, we estimate a truncated regression equation in the second stage. The DEA efficiency scores obtained from the first-stage DEA analysis are termed raw scores as they do not reflect each sampled MFI's specific operating characteristics or

[5] Pitfalls 3.1, 3.2, 4.1, 4.3 and 5.1

[6] As a referee has noted, the number of active borrowers has deficiencies as a social performance measure because it ignores both quality and loan size. See the discussion in Copestake (2007) and Bibi, Balli, Matthews & Tripe (2018). Until such time as superior measures can be developed, which are not ratios (which would be problematic for use in DEA), however, we are obliged to follow many prior researchers in using it.

[7] The term "super-efficiency" relates to an amended DEA model in which DMUs can obtain efficiency scores greater than one because each DMU is not permitted to use itself as a peer. This model is used for ranking efficient units. For further detail see (Coelli et al., 2005, pp. 200-201).

managerial and operational factors which may or may not be under the control of microfinance management. We therefore use the second stage regression approach advocated by Fried, Schmidt and Yaisawarng (1999). Truncated regression (as per Simar & Wilson, 2007) is used to model the dependent variables.

$$\theta_{ikt} = \alpha_0 + C_{ikt}\beta + Z_{ikt}\gamma + \varepsilon_{ikt} \quad \text{(Equation 4)}$$

This equation can be understood as the first-order approximation of the unknown true relationship. θ_{ikt} is the efficiency score of microfinance institution i, located in country k, in year t. α_0 is a constant, C_{ikt} is a vector of control variables for microfinance institution i and country k. These variables include MFI age, MFI size, real GDP, inflation and portfolio at risk greater than 30 days (PAR 30). Z_{ikt} are the exogenous (governance and gender) variables expected to be associated with efficiency scores. These governance and gender variables[8] are suggested by Müller & Uhde (2013) and Barry & Tacneng (2014). Governance variables include ownership structure (dummy for non-profit-oriented and PFMs) and regulatory structure (dummy for regulated) of MFIs (as suggested by Hartarska, 2005; Hartarska & Mersland, 2012; Mersland & Strøm, 2009). Others are corruption control and political stability (developed by Kaufmann, Kraay, & Massimo, 2009). These governance variables range along a scale of approximately −2.5 to 2.5, where −2.5 indicates very weak institutional quality. The parameters β and γ are vectors of coefficients. ε_{ikt} is the error term.

We follow the Simar and Wilson (2007) methodology. However, we alter our method in following ways. First, we run the model (Equation 4) by including year as a trend variable and then include year as fixed effects, recognising that when we run truncated regressions (Simar & Wilson, 2007), we are ignoring the firm effects and creating omitted variable bias in our analysis. We have done all the necessary tests i.e. FE (fixed firm effect and time fixed effects) versus random effects with Hausman and Wald tests and find that they strongly support the inclusion of time effects and firm effects for most of the regressions. Second, as our data is a panel, ignoring the fixed firm effect for each MFI might produce biased results. In this panel setup, therefore, we added both firm and time fixed effects rather than just adding time effects as in truncated regression.

[8] We considered 6 governance factors, but 4 are highly correlated with each other or with control variables leaving us with only two governance variables to use in our regression model.

3. Data description

We perform a two stage analysis; calculating DEA efficiency scores and then applying regression analysis. Our data sources are MIX market and World Bank indicators. Data on governance factors is also downloaded from the database of the World Bank. The variables are explained in Table 1. Descriptive statistics are presented in Table 2 and correlation among variables is presented in Table 3. In the first stage, we use balanced panel data as suggested in Dyson et al. (2001) to provide consistency in efficiency scores between years. This reduces our data sample to 101 MFIs from 2005 to 2012. The dataset is also used for the second stage analysis, but here we use unbalanced panel data for the period of eight years from 2005 to 2012.

[INSERT TABLE 1 ABOUT HERE]

Overall, the distributions of observations of MFIs between the sample countries are 35% from India, 27% from Bangladesh, 18% from Nepal, 14% from Pakistan and 6% from Sri Lanka. These MFIs include banks, credit unions or cooperatives, non-bank financial institutions (NBFIs), NGOs and other institutions. We split them into non-profit-oriented and profit-oriented institutions[9], comprising 65% and 35% of the whole sample respectively. Furthermore, in our dataset 64% of MFIs are regulated and 36% non-regulated. The PFMs (percentage of female board members), PFOs (percentage of female loan officers) and PFBs (percentage of female borrowers) in each of the sample countries are presented in Figure 1.

[INSERT FIGURE 1 ABOUT HERE]

[INSERT TABLE 2 ABOUT HERE]

Table 2 provides the summary statistics for variables used in the first and second stage analysis. The maximum and minimum values of these variables show a lot of variation between observations. For example, the minimum number of personnel working in MFIs is 4 with an average of 1,478 and the minimum number of active borrowers is 58 with an average of 343,747. These suggest a wide range for each variable and prompt the use of robust regression methods as a check on robustness to outliers.

[9] Non-profit-oriented MFIs include NGOs, credit unions and institutions categorized as 'others' and the category of profit-oriented MFIs include banks, rural banks and NBFIs.

[INSERT TABLE 3 ABOUT HERE]

Table 3 reports the correlation coefficients between the estimated efficiency scores and the explanatory variables. This identifies the basic relationships among all variables and explores potential multi-collinearity, which is not identified.

4. Results

Results using models from Equations 1, 2, 3 and 4 are presented as follows. The first stage DEA efficiency scores (bootstrapped and non-bootstrapped) of South Asian MFIs are reported in section 4.1, while the impact of governance and gender on these efficiency scores is described in section 4.2.

4.1. First Stage Efficiency Estimates

The average efficiency estimates for all DEA models are reported in Table 4. The scores in column (A) are original DEA efficiency estimates before outlier identification, while column (B) shows the efficiency estimates after deleting the outliers. In column (C) bias-corrected bootstrap estimates are reported using the data with the outliers deleted. We find that after deleting the outliers, the efficiency scores increase, but decrease after applying the bootstrap technique. Efficiency estimates from traditional DEA models overestimate the TE (technical efficiency) scores that ultimately affect the second stage analysis (Simar & Wilson, 2007).

[INSERT TABLE 4 ABOUT HERE]

[INSERT TABLE 5 ABOUT HERE]

In the first stage analysis, we decompose[10] the financial and social efficiency scores into TE and SE as presented in Table 5. We categorized our sample across countries, years, ownership and regulatory structure. The efficiency levels in sample countries are according to our expectation that, in spite of working in similar economic environments, efficiency levels of South Asian MFIs vary from each other. No institution appears efficient in any model for

[10] We have estimated the BCC (VRS) input (output) oriented models for financial (social) efficiency of MFIs using pooled data. Mean values of these scores are reported for the individual sub-samples. There is not much difference between the economic conditions of South Asian MFIs, so we did not test the sub-samples individually. Dyson et al. (2001) highlight the homogeneity assumption with each sub-sample run in single capacity — each DMU will make an efficiency score by comparing itself with a similar group (for more detail, see Tulkens & Eeckaut, 1995). Detailed efficiency scores of pooled data for each MFI is available from the authors on request.

all years consistently. In the ownership structure category, we find that non-profit-oriented MFIs are more socially efficient than profit-oriented MFIs, which are more financially efficient. In the regulatory structure category, we find that non-regulated MFIs are more socially efficient and regulated MFIs are more financially efficient. The difference between these sub-samples is significant. Overall, we can see that South Asian MFIs appear scale efficient, but technically inefficient. Low scores for TE show that MFIs are not utilizing their resources efficiently to generate the required output levels, rather than being due to scale.

4.2. Second Stage Regression Analysis

Although the first stage efficiency scores are interesting on their own, we also seek to identify some key determinants of the differences in MFIs' efficiency scores. Tables 6 and 7 provide the results of key determinants of financial and social efficiency, respectively. We hold the control variables fixed and introduce all the other governance and gender variables in this main set, in order to check the stability of the coefficients of these governance and gender measures.

As explained in the methodology section, we run our model by including year variable as a trend variable and then including year as fixed effects. It gives us three sets of results; truncated regressions (Simar & Wilson, 2007), panel regressions with random effect while including time dummies and panel regressions with fixed effect clustered on MFIs while including time dummies. Although we report all three sets of results, our econometrics tests convince us to include time fixed effects in regressions. We therefore comment mostly on the third set of results in tables 6 and 7. Moreover, we find that the fixed effects model is mostly favourable and results are consistent with theory (although not statistically significant). Whenever the Hausman test fails to reject the null hypothesis then both fixed and random effects produce similar results, both very different to those from the truncated regression.

[INSERT TABLE 6 ABOUT HERE]

[INSERT TABLE 7 ABOUT HERE]

The bootstrapped financial and social efficiency scores are dependent variables for Tables 6 and 7 respectively. A number of control variables show interesting implications, generally in line with previous research linking governance variables to firms' market conditions. Size of

MFIs is positive and highly significant in all regressions of financial and social efficiency, confirming the findings of Kyereboah-Coleman and Osei (2008). This is because a large firm has the ability to enhance productivity through diversification of products and services and to accommodate risk. Real GDP (size of country) has a negative impact on both financial and social objectives of MFIs: when real GDP increases, MFIs' efficiency deteriorates. In terms of social efficiency, this is reasonable in that the social objectives of MFIs are being achieved with MFIs actually working in the right direction.

In the case of financial efficiency, the reduction in efficiency is unexpected. It can be argued, however, that increases in GDP denote economic growth. A growing economy may offer an expanded set of economic opportunities for its residents some of whom may be the poor being served by the MFIs. The ensuing dynamics may then push some MFI clients up the economic ladder and out of the purview of the MFIs. This 'loss of business' can weaken the balance sheets of the MFIs and eventually show up in diminished financial performance. The negative relationship of PAR30 with MFI efficiency might suggest that the efficiency of these MFIs decreases due to adopting riskier loans, suggesting the importance of MFI social-orientation. The risk ratio results are according to our expectations that having riskier loans negatively impacts the efficiency of MFIs.

We find an inverse impact of external governance on financial and social efficiency. Political stability appears positively significant for both financial and social efficiency regressions. As in the descriptive statistics, these variables all have negative values in the data sets (showing a low level of governance), but the positive signs in the regressions show a positive effect of these variables on efficiency. This is consistent with Müller and Uhde (2013), who find a country's external governance to have a positive impact on financial sustainability, and a negative impact on social objectives, in line with our findings. However, our results are not consistent with the findings of Barry and Tacneng (2014), as they find that weak governance favours relationship-based lending to insiders rather than rule-based lending.

The dominant finding in gender literature seems to be that performance improves with more women in management and on the board (Strøm et al., 2014). However, our results show that among gender variables, PFOs, as expected, have a positive impact on financial and social efficiency (consistent with Beck et al., 2018) while, surprisingly, contrary to Strøm et al. (2014), PFMs have no significant impact on the efficiency indicators. Our findings in the case

of female borrowers are inconsistent with Hermes et al. (2011), who find a negative impact of female borrowers on efficiency. Our findings for female managers in general support arguments for high ability among female MFI leaders due to a superior match of tasks. The firm controls show that the firm effects are reasonably consistent, being positive for MFI size in both financial and social regressions.

5.3 Robustness Analysis

How reliable are the above results? In the first robustness test, we estimate the first stage efficiency scores using different output variables, such as interest revenue for financial efficiency (along with Gross Loan Portfolio (GLP)) and PFBs (along with GLP), and find a very similar pattern of efficiency scores (see Appendix 1). Secondly, our ambivalent results for female directors motivated alternative tests employing different specifications. To check the robustness of our second stage female variables, we thought that women on the board might mean that MFIs follow a less risky strategy reflected, in turn, in lower revenues (and thus lower financial efficiency according to our existing specification). Some adjustment or control for risk in the regression might therefore be useful. We use PAR 30 and 90 and risk coverage as risk ratios and interact them with female variables (see Appendix 2) using the methodology as explained in Balli and Sørensen (2013).

We report results for both truncated regressions and panel fixed effect regressions (Hausman tests give highly significant results favoring this technique with both a general interaction term methodology (method 1) and with the Balli & Sørensen (2013) correction (method 2)). When we include the PAR 30 interaction term, we find that correcting with panel fixed effects and method 2 we have no evidence for interaction terms being significant for gender factor or PAR 30 variables.

Thirdly, as we find a negative link between real GDP and efficiency, we check whether this is due to Sri Lanka being relatively more economically advanced than other South Asian countries. We therefore re-run the model with Sri Lanka omitted, but results remain the same. In unreported regressions, we also run the Tobit model, omitting Sri Lanka (as it has a relatively larger real GDP per capita) and simple GLS regression with both fixed effects and

random effects, but find no material difference in results from those presented here. The robustness checks confirm our results when we change the model and vary the specifications, upholding our conclusions for the link among governance, gender and efficiency.

Last, our calculated efficiency index is mostly within expected limits (0 to 1) and we only truncate a few (or none most of the time) observations depending on the regressor set in each equation calculated for both truncated regressions setup and panel setup. Therefore, in terms of consistency and biasedness using the panel setup produces robust results as well.

5. Conclusion

MFIs are remarkable in that they elect more female chairs and female directors than financial institutions in advanced countries do. A MFI's mission is to supply loans to small businesses, especially women, in the developing world, and it aims to do so in a financially sustainable manner. This paper investigates the conditions under which female roles tend to emerge, and their relationships with the financial and social performance of MFIs as found in Mersland and Strøm (2014).

We apply DEA to panel data (annual observations from 2005 to 2012) to evaluate the efficiency of 101 MFIs of South Asian countries. The first research question of this paper asks about the technical and scale efficiency levels of South Asian MFIs. To answer the first research question, we assess bootstrapped TE and SE at the first stage of our analysis. Our findings show that South Asian MFIs are technically inefficient but scale efficient. We can see that scale efficiency is not hugely important, and that, as expected, financial efficiency is higher on average than social efficiency. It would be reasonable to argue that there was some improvement in financial efficiency over time, however we note that the relatively low average efficiency scores show that there is quite a bit of variation in microfinance efficiency. The second research question was about identifying the factors that explain the variation in microfinance efficiency and to explore those factors we include governance and gender variables as possible key determinants of MFIs' efficiency. In order to explain the likely impacts of efficiency scores on variations in microfinance efficiency, we conduct a second stage regression analysis using a truncated bootstrapped regression model. Second stage findings show that female loan officers are positive determinants of MFIs' efficiency, while female borrowers and female board members show no clear effect. Similarly, internal

corporate governance factors appear (mostly) to be a positive determinant of MFIs' efficiency but external corporate governance factors are negative determinants of MFIs' efficiency.

Although we have advanced the existing empirical literature in several ways as described in the introduction, our methodological approach has also incorporated more current techniques, with use of bootstrapped efficiency scores and truncated regressions. However, there are still ways in which the research reported in this paper could be extended in future research. Firstly, the sample size in this study is restricted by data availability, choice of statistical analysis, time and MFIs covered so results must be carefully handled since many factors can affect MFIs' efficiency. It would be desirable to extend the present study by inclusion of other corporate governance and gender variables. More research on board practices is needed to assess the effects on MFIs' efficiency levels. Secondly, we believe that mostly contrasting governance and performance results are because MFIs are young firms and the optimal governance form has perhaps not been settled. Future research would also benefit from exploring the extent and the implications of females' attributes, like education and experience.

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Table 1: Definition of input and output variables for efficiency evaluation using DEA

Specification	Indicators	Definition	Data Sources
First-stage DEA models			
Input variables for financial and social efficiency	Personnel	Number of employees actively employed by the MFI. This includes contract employees, advisors who dedicate most of their time to the microfinance institution even though they are not on the MFIs' rosters of employees.	MIX Market
	Operating expenses	Administrative expenses excluding interest expense.	
	Financial expenses	These expenses continue to be classified by associated liability, but are also broken down by type of expense (interest, fee) for each associated financial liability.	
Output variables for social efficiency	Number of active borrowers	The numbers of individuals or entities who currently have an outstanding loan balance with the MFI or are primarily responsible for repaying any portion of the Loan Portfolio, Gross. Individuals who have multiple loans with an MFI should be counted as a single borrower.	
	Female borrowers	Number of female borrowers among number of active borrowers	
Output variable for financial and social efficiency	Gross loan portfolios	All outstanding principal for all outstanding client loans including delinquent, new and restructured loans. But this item does not include the written off loans and it also excludes the interest receivable and employee loans.	
Output variables for financial efficiency	Financial revenues	Revenues from the loan portfolio and from other financial assets are broken out separately and by type of income (interest, fee).	
	Interest revenue	Interest revenue on the loan portfolio	
Second-stage explanatory variables			
Institution-specific variables	Dummy of mature MFIs (DMATURE)	Dummy of mature takes the value of one when the age of operation of MFIs is equal to or greater than 8 years old and zero otherwise. MIX classifies MFIs into three categories of age (new, young and mature) based on the maturity of their microfinance operations. This is calculated as the difference between the year they started their microfinance operations and the year of data submitted by the institutions. We combined new and young in one category (base dummy) that represents the MFIs with fewer than eight years in operation and mature MFIs that have 8 or more years in operation in the other.	
	Size of institutions (LAST)	Logarithmic values of total assets	
	Risk coverage ratio (%) (RSKC)	Impairment loss allowance divided by portfolios at risk greater than 30 days.	
	Portfolios at risk greater than 30 days (%) (PAR30)	The value of all loans outstanding that have one or more instalments of principal past due more than 30 days. This includes the entire unpaid principal balance, including both the past due and future instalments, but not accrued interest. It also includes loans that have been restructured or rescheduled.	
Country-specific/environmental variables	Log of Real GDP (LGDP)	Logarithmic value of real GDP that is used as a proxy to measure the size of an economy.	World Bank
	Inflation, consumer prices (annual %) (INFL)	Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly.	
Governance indicators	Internal indicator: Percentage of female board members (%) (PFMs)	Number of women board members divided by total board members.	MIX Market
	Internal indicator: Dummy of non-profit-oriented MFIs	This is a dummy variable that is equal to one if the MFI is a non-profit-oriented institution and zero otherwise	
	Internal indicator: Dummy of regulated	This is a dummy variable that is equal to one if the MFI is listed as a regulated institution and zero otherwise	
	External indicator: Political stability and absence of violence and terrorism	Reflects perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism. Estimate of governance ranges from approximately -2.5 (weak) to 2.5 (strong) governance performance.	World Bank
	External governance indicator: Control of corruption	Reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Estimate of governance ranges from approximately -2.5 (weak) to 2.5 (strong) governance performance.	
Gender variables	Percentage of female loan officers (%) (PFOs)	Number of women loan officers divided by total loan officers	MIX Market
	Percentage of female borrowers (%) (PFBs)	Number of women active borrowers divided by number of active borrowers	

Notes: Variables are explained as defined in their respective data sources.

Table 2: Descriptive statistics for efficiency evaluation using DEA

Variable	Mean	Min.	Max.	Std. Dev	Skewness	Kurtosis
First stage DEA model input variables						
Personnel	1,478	4	34,841	4,053	4.43	22.61
Operating expenses	4,778,091	2,256	117,256,574	13,669,223	4.53	24.52
Financial expenses	3,893,606	1,084	157,735,748	14,174,387	6.93	64.12
First stage DEA model output variables						
Gross loan portfolio	42,556,877	8,786	1,007,989,551	12,748,144	4.51	23.82
Financial revenue	11,105,578	3,552	322,123,003	35,066,484	4.38	21.75
Number of active borrowers	334,747	58	6,710,000	1,036,423	4.88	27.42
Interest fee	5,501,514	3,378	150,172,100	17,135,417	4.43	22.61
Female borrowers	306,422	58	6,457,033	964,020	4.68	24.57
Second stage explanatory variables						
Dummy of mature MFIs	0.86	0.00	1.00	0.35	-2.53	7.39
Dummy of Regulated MFIs	0.68	0.00	1.00	0.48	-0.56	1.31
Dummy of non-profit-oriented MFIs	0.64	0.00	1.00	0.48	-0.86	1.74
Assets ($m)	59.30	0.04	1,090.00	179.00	4.24	21.40
Real GDP	3,361	1,667	8,855	1,473	0.63	2.74
Inflation (%)	8.73	3.47	22.56	3.08	1.46	7.71
Political stability and absence of violence/terrorism	-1.54	-2.81	-0.69	0.46	-1.63	5.27
Control of corruption	-0.72	-1.42	-0.09	0.32	-0.03	2.09
Percentage of female board members (%)	32.8	6.70	100.00	19.30	134.70	482.00
Percentage of female loan officers (%)	31.50	0.50	100.00	27.90	118.50	331.00
Percentage of female borrowers (%)	88.10	2.60	100.00	21.80	-186.40	534.00
Portfolios at risk greater than 30 days (%)	8.20	0.10	71.00	34.00	564.00	435.90
Portfolios at risk greater than 90 days (%)	5.99	0.10	97.00	12.00	458.00	297.20
Risk coverage ratio (%)	2.08	0.00	40.31	3.85	970.00	368.00

Note: Variables are defined in Table 1.

Table 3: Correlation among second stage variables relative to DEA analysis

	FCCI	SCCO	DMATURE	LAST	LGDP	INFL	REG	NBFI	CORCNT	STAB	PFMA	PFOA	PFBs	PAR 30	PAR 90	RISKC
FCCI	1															
SCCO	0.35	1														
DMATURE	-0.06	-0.13	1													
LAST	-0.19	-0.08	0.08	1												
LGDP	-0.05	0.02*	-0.04	-0.03	1											
INFL	-0.01	-0.03	0.04	0.01	0.32	1										
REG	0.02**	0.05*	-0.10	-0.07	-0.17	0.07	1									
NBFI	0.13	-0.04	0.25	-0.12	-0.18	-0.05	-0.37	1								
CORCNT	-0.13	0.04	-0.19	-0.09	0.58***	-0.00	-0.08**	-0.31	1							
STAB	-0.16	-0.01	0.00	0.08	0.18**	-0.42	-0.31***	-0.01	0.48	1						
PFMA	0.09	0.01**	0.06	0.02	-0.01	0.05	-0.05	0.18	-0.12	-0.14	1					
PFOA	0.00**	-0.03	0.00*	-0.12	0.19	0.11	0.03	-0.00	0.13**	-0.09	0.05	1				
PFBs	0.08	0.03	0.03	0.04**	-0.19	-0.21	-0.21	0.09	0.05	0.33*	0.04*	-0.01	1			
PARR30	0.01*	0.01*	0.05	-0.01	0.08**	0.02	0.04***	-0.09	0.02*	0.02	-0.03	0.00*	0.00	1		
PARR90	0.12*	-0.00	0.09*	0.03	0.02	0.02	0.03	-0.09	-0.04	-0.03	0.05*	-0.01	0.02**	0.41*	1	
RISKC	0.03	-0.01	-0.02	-0.03	0.01	-0.02	-0.04	0.06	0.01	-0.05	0.03	-0.05	0.11*	-0.05*	-0.05	1

Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Correlations among second stage variables are presented. FCCI and SCCO are dependent variables of financial and social efficiency scores. FCCI is financial efficiency score that is calculated using variable returns to scale and input oriented model and SCCO is social efficiency score that is calculated using variable returns to scale and output oriented model. DMATURE is the dummy indicator for mature institutions. LAST = logarithm of assets, LGDP = logarithm of real GDP, INFL = inflation, REG = regulated MFIs dummy, NBFI = non-profit-oriented MFIs dummy, CORCNT = corruption control, STAB = political stability, PFMA = Average value of percentage of female board members, PFOA = Average value of percentage female loan officers, PFBs = percentage of female borrowers.

Table 4: Average DEA efficiency scores

	(A)	(B)	Difference	(C)	Difference
Financial			(A-B)		(B-C)
BCC-I	0.53	0.63	-0.11***	0.56	0.06***
BCC-O	0.54	0.64	-0.10***	0.59	0.05***
CCR-I/O	0.48	0.55	-0.07***	0.49	0.07***
Input oriented scale efficiency	0.92	0.89	0.03***	0.88	0.01**
Output oriented scale efficiency	0.91	0.87	0.04***	0.85	0.00***
Social					
BCC-I	0.51	0.51	-0.01	0.44	0.06***
BCC-O	0.51	0.52	-0.00	0.45	0.06***
CCR-I/O	0.45	0.45	-0.00	0.39	0.06***
Input oriented scale efficiency	0.92	0.92	-0.00	0.89	0.02**
Output oriented scale efficiency	0.91	0.91	0.00	0.88	0.00**
Observations	824	808		808	

Notes: BCC and CCR denote variable returns to scale and constant returns to scale respectively. 'I' refers to input-oriented model and 'O' refers to output-oriented model. Column A shows efficiency estimates of contaminated data, before deleting outliers, column B shows efficiency estimated after outliers deleted, and column C shows bootstrapped efficiency estimates using uncontaminated data. Mann-Whitney test and independent t-test are used for statistical significance of differences. Differences may not be exact because of rounding errors.

Table 5: Sub-groups efficiency scores from DEA approach

	Observations	FBCC-I	SBCC-O	FSCALE-I	SSCALE-O
All sample	808	0.563	0.453	0.877	0.884
Across country					
Bangladesh	216	0.528	0.465	0.842	0.859
India	280	0.591	0.439	0.879	0.864
Nepal	144	0.591	0.509	0.922	0.921
Pakistan	112	0.530	0.383	0.879	0.918
Sri Lanka	56	0.551	0.478	0.879	0.918
Across time					
2005	101	0.517	0.453	0.877	0.868
2006	101	0.521	0.471	0.893	0.886
2007	101	0.543	0.420	0.891	0.895
2008	101	0.542	0.458	0.882	0.872
2009	101	0.582	0.462	0.874	0.883
2010	101	0.594	0.452	0.865	0.882
2011	101	0.604	0.452	0.860	0.885
2012	101	0.598	0.457	0.871	0.901
Ownership structure					
Profit-oriented	280	0.590	0.443	0.869	0.885
Non-profit-oriented	528	0.548	0.459	0.881	0.883
Difference		0.04***	-0.02	-0.01*	-0.00
Regulatory structure					
Regulated	520	0.568	0.445	0.874	0.883
Non-regulated	288	0.553	0.468	0.882	0.886
Difference		0.02*	-0.02*	-0.01	-0.00

Note: FBCC-I denotes financial variable returns to scale using an input-oriented model, and SBCC-O denotes social variable returns to scale using an output-oriented model. FSCALE-I denotes financial scale efficiency using an input-oriented model, and SSCALE-O denotes social scale efficiency using an output-oriented model. Mann-Whitney test and independent t-test are used for statistical significance of difference values.

Table 6: Financial efficiency regressions using DEA efficiency estimates

	I			II			III			IV		
	Truncated	Panel RE	Panel FE	Truncated	Panel RE	Panel FE	Truncated	Panel RE	Panel FE	Truncated	Panel RE	Panel FE
	0.015	-0.016	-0.020	0.017	-0.016	-0.023	0.005	-0.055**	-0.060*	0.002	-0.044*	-0.054*
DMATURE	(0.44)	(0.45)	(0.40)	(0.38)	(0.43)	(0.31)	(0.82)	(0.04)	(0.05)	(0.93)	(0.08)	(0.07)
	0.018***	0.030***	0.045***	0.018***	0.027***	0.043***	0.023***	0.037***	0.060***	0.022***	0.034***	0.060***
Log of assets	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	-0.031*	-0.009	0.104	-0.056**	-0.004	0.075	-0.056**	-0.029	0.003	-0.115***	-0.042	-0.064
Log of real GDP	(0.09)	(0.80)	(0.54)	(0.02)	(0.92)	(0.66)	(0.02)	(0.52)	(0.99)	(0.00)	(0.39)	(0.75)
	-0.027	-0.025	-0.030	-0.000	-0.008	-0.015	-0.041	0.005	-0.007	0.021	0.015	0.083
Inflation	(0.26)	(0.21)	(0.13)	(0.98)	(0.68)	(0.46)	(0.14)	(0.82)	(0.74)	(0.49)	(0.35)	(0.64)
	-0.000	0.027		0.072	0.023		0.022	0.069*		0.042**	0.070*	
Non-profit-oriented	(0.98)	(0.39)	-	(0.68)	(0.46)	-	(0.33)	(0.07)	-	(0.04)	(0.06)	-
	-0.028*	-0.017		-0.021	-0.005		-0.037*	-0.006		-0.023	0.003	
Regulated	(0.07)	(0.60)	-	(0.21)	(0.88)	-	(0.05)	(0.86)	-	(0.18)	(0.94)	-
	-0.005	-0.011	-0.012	-0.004	-0.010	-0.011	-0.018	-0.059*	-0.063*	-0.018	-0.057*	-0.061*
Portfolios at risk greater than 30 days	(0.89)	(0.57)	(0.55)	(0.91)	(0.60)	(0.59)	(0.77)	(0.08)	(0.09)	(0.75)	(0.09)	(0.09)
				0.040*	-0.038	-0.065				0.070	0.005	-0.033
Control of Corruption	-	-	-	(0.25)	(0.33)	(0.16)	-	-	-	(0.10)	(0.91)	(0.50)
				0.025	0.050***	0.059**				0.066**	0.044*	0.055*
Political stability and Absence of violence	-	-	-	(0.24)	(0.02)	(0.03)	-	-	-	(0.01)	(0.09)	(0.09)
Percentage of female board members (average 2008 to 2012)	-	-	-	-	-	-	-0.054 (0.19)	-0.072 (0.24)	-0.069 (0.37)	-0.021 (0.61)	-0.060 (0.34)	-0.066 (0.43)
Percentage of female loan officers (average 2008 to 2012)	-	-	-	-	-	-	0.096*** (0.00)	0.087 (0.16)	0.160 (0.10)	0.106*** (0.00)	0.090 (0.14)	0.144 (0.14)
Percentage of female borrowers	-	-	-	-	-	-	-0.163*** (0.00)	-0.066 (0.16)	0.016 (0.67)	-0.213*** (0.00)	-0.080 (0.13)	0.022 (0.58)
Sample	589	589	589	589	589	589	440	440	440	440	440	440
Firm Fixed Effect	-	No	Yes	-	No	Yes	-	No	Yes	-	No	Yes
Time Dummies included	-	Yes	Yes	-	Yes	Yes	-	Yes	Yes	-	Yes	Yes
Wald Test (p-value)	-	0.000	0.000	-	0.000	0.001	-	0.001	0.004	-	0.000	0.001
Hausman Test (p-value)	-	-	0.998	-	-	0.000	-	-	0.013	-	-	0.602

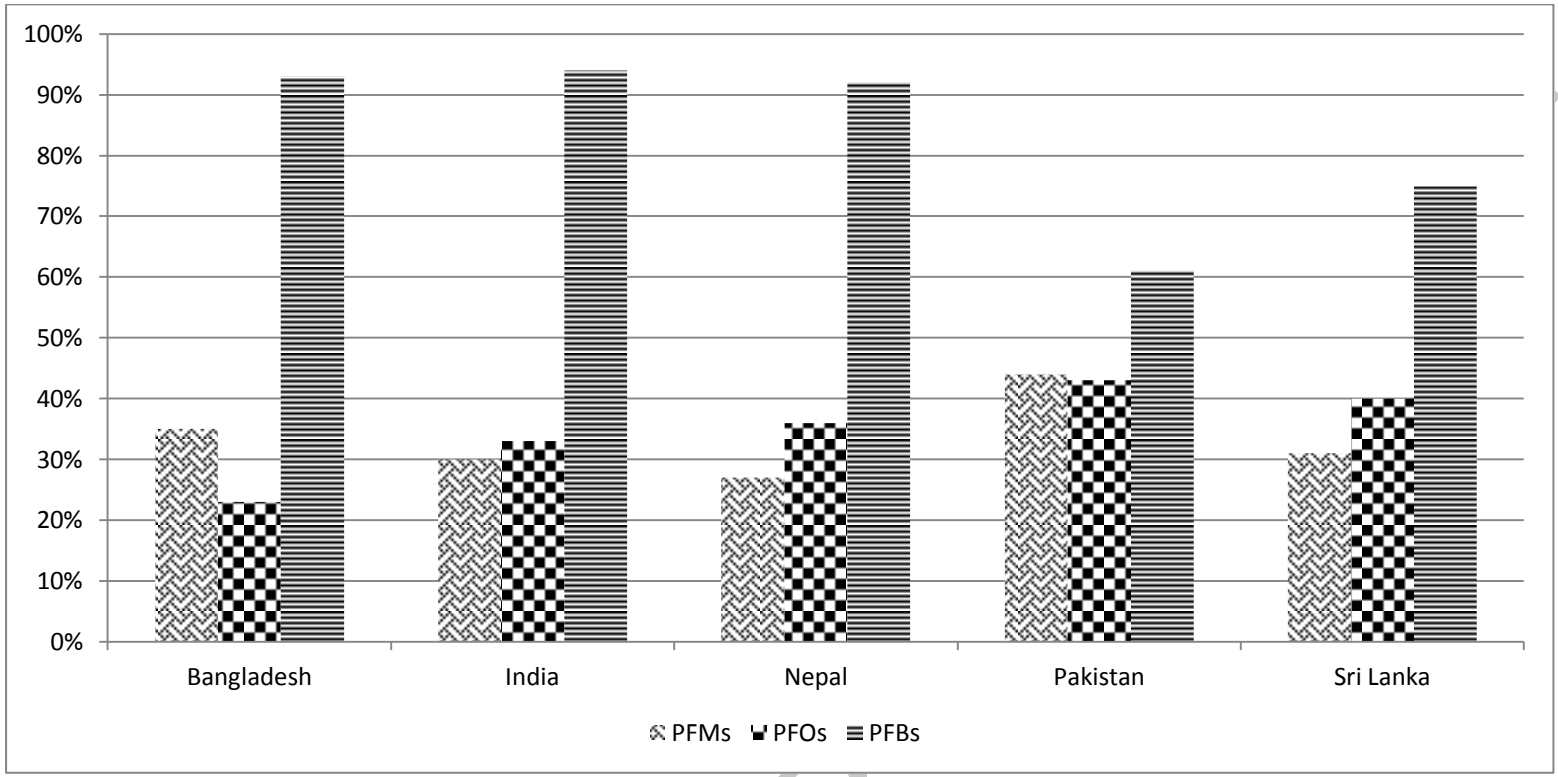
Note: Technical bootstrapped financial efficiency (variable returns to scale – input oriented) is the dependent variable. *, **, and *** indicate significance level of coefficients at the 10%, 5% and 1%, respectively. The truncated regression analysis with bootstrapping (Simar & Wilson, 2007) results above was derived from 1000 bootstrapped iterations. Panel RE and Panel FE denotes Panel regressions with random effect while including time dummies and Panel regressions with fixed effect clustered on MFI's while including time dummies respectively. Wald test is calculated for the null hypothesis that time effect is not significant. Hausman Test is calculated only for Panel data analysis for the null hypothesis that panel FE and panel RE have similar coefficients against the alternative hypothesis that Panel FE is favourable. Constant is included but not reported to all the regressions. Coefficient of Inflation is multiplied by 10. Year variable as a trend is included in truncated regressions but not reported.

Table 7: Social Efficiency regressions using DEA efficiency estimates

	I			II			III			IV		
	Truncated	Panel RE	Panel FE	Truncated	Panel RE	Panel FE	Truncated	Panel RE	Panel FE	Truncated	Panel RE	Panel FE
	0.007	-0.011	-0.007	0.008	-0.012	-0.011	0.005	-0.042	-0.045	0.002	-0.034	-0.041
DMATURE	(0.75)	(0.63)	(0.78)	(0.69)	(0.60)	(0.64)	(0.84)	(0.12)	(0.15)	(0.94)	(0.20)	(0.17)
	0.028***	0.034***	0.043***	0.027***	0.030***	0.040***	0.030***	0.041***	0.056***	0.029***	0.037***	0.056***
Log of assets	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	-0.027	-0.008	0.166	-0.050*	0.002	0.135	-0.048**	-0.018	0.050	-0.107***	-0.019	-0.015
Log of real GDP	(0.12)	(0.81)	(0.29)	(0.05)	(0.95)	(0.38)	(0.02)	(0.69)	(0.79)	(0.00)	(0.70)	(0.93)
	-0.021	-0.014	-0.018	0.014	0.006	0.001	-0.041*	-0.007	-0.001	0.023	0.010	0.004
Inflation	(0.40)	(0.36)	(0.25)	(0.62)	(0.66)	(0.92)	(0.12)	(0.72)	(0.64)	(0.43)	(0.49)	(0.81)
	0.010	0.035		0.016	0.028		0.032	0.072*		0.052**	0.068*	
Non-profit-oriented	(0.54)	(0.27)	-	(0.36)	(0.38)	-	(0.13)	(0.07)	-	(0.02)	(0.08)	-
	-0.023	-0.007		-0.013	0.008		-0.030*	0.001		-0.016	0.010	
Regulated	(0.14)	(0.83)	-	(0.41)	(0.81)	-	(0.08)	(0.98)	-	(0.33)	(0.79)	-
	0.002	-0.007	-0.009	0.003	-0.006	-0.007	0.000	-0.042	-0.046	-0.000	-0.041	-0.045
Portfolios at risk greater than 30 days	(0.95)	(0.66)	(0.58)	(0.93)	(0.71)	(0.63)	(0.99)	(0.14)	(0.14)	(0.99)	(0.15)	(0.14)
				0.026	-0.059	-0.086**				0.068*	-0.026	-0.062
Control of Corruption	-	-	-	(0.48)	(0.10)	(0.03)	-	-	-	(0.09)	(0.50)	(0.14)
				0.039*	0.063***	0.069***				0.070**	0.051*	0.061*
Political stability and Absence of violence	-	-	-	(0.05)	(0.00)	(0.01)	-	-	-	(0.01)	(0.05)	(0.06)
Percentage of female board members (average 2008 to 2012)	-	-	-	-	-	-	-0.062* (0.09)	-0.065 (0.29)	-0.026 (0.69)	-0.029 (0.48)	-0.055 (0.38)	-0.021 (0.77)
Percentage of female loan officers (average 2008 to 2012)	-	-	-	-	-	-	0.091*** (0.00)	0.078 (0.21)	0.177** (0.05)	0.109*** (0.00)	0.082 (0.19)	0.159* (0.08)
Percentage of female borrowers	-	-	-	-	-	-	-0.146*** (0.00)	-0.036 (0.42)	0.038 (0.29)	-0.197*** (0.00)	-0.053 (0.29)	0.039 (0.28)
Sample	589	589	589	589	589	589	440	440	440	440	440	440
Firm Fixed Effect	-	No	Yes	-	No	Yes	-	No	Yes	-	No	Yes
Time Dummies included	-	Yes	Yes	-	Yes	Yes	-	Yes	Yes	-	Yes	Yes
Wald Test (p-value)	-	0.000	0.000	-	0.000	0.000	-	0.000	0.011	-	0.000	0.048
Hausman Test (p-value)	-	-	1.000	-	-	0.683	-	-	0.805	-	-	0.004

Note: Technical bootstrapped social efficiency (variable returns to scale – output oriented) is the dependent variable. *, **, and *** indicate significance level of coefficients at the 10%, 5% and 1%, respectively. The truncated regression analysis with bootstrapping (Simar & Wilson, 2007) results above was derived from 1000 bootstrapped iterations. Panel RE and Panel FE denotes Panel regressions with random effect while including time dummies and Panel regressions with fixed effect clustered on MFI's while including time dummies respectively. Wald test is calculated for the null hypothesis that time effect is not significant. Hausman Test is calculated only for Panel data analysis for the null hypothesis that panel FE and panel RE have similar coefficients against the alternative hypothesis that Panel FE is favourable. Constant is included but not reported to all the regressions. Non-profit-oriented and Regulated dummies are dropped from Panel FE regressions due to perfect correlations with fixed effect dummies. Coefficient of Inflation is multiplied by 10. Year variable as a trend is included in truncated regressions but not reported.

Figure 1: Proportion of females in MFIs of each sample country



Appendix 1: Average efficiency scores

	Efficiency estimates				Bias-corrected efficiency estimates				
	Mean	SD	Min	Max	Mean	SD	Min	Max	Observations
Financial efficiency (using Financial revenues)	1.754	0.594	1.000	6.221	1.933	0.641	1.082	6.949	808
Financial efficiency (using Interest fee)	2.514	1.223	1.000	15.002	2.817	1.340	1.069	16.270	808
Social efficiency (using number of active borrowers)	2.382	2.276	1.000	59.214	2.656	3.236	-1.567	88.242	808
Social efficiency (using percentage of female borrowers)	2.000	1.259	1.000	9.158	1.190	1.912	-11.947	11.018	808

Notes: Efficiency estimates using general method and bias corrected (bootstrap) are reported with different combinations of inputs and outputs.

Appendix 2: Interaction effects of risk ratios - Portfolios at risk greater than 30 days

	Financial				Social			
	Method-1		Method-2		Method-1		Method-2	
	Truncated	Pane FE	Truncated	Pane FE	Truncated	Pane FE	Truncated	Pane FE
Dummy of mature	-0.003	-0.026	-0.005	-0.032	-0.006	-0.023	-0.009	-0.028
Log of assets	0.044***	0.074***	0.043***	0.072***	0.045***	0.076***	0.044***	0.075***
Log of real GDP	-0.059***	-0.238	-0.058***	-0.226	-0.058**	-0.249	-0.057*	-0.239
Inflation	-0.002	0.001	-0.003	0.000	-0.002	0.001	-0.002	0.000
Regulated MFIs	-0.037**	-	-0.040**	-	-0.038**	-	-0.041***	-
Non-profit-oriented MFIs	-0.002	-	-0.003	-	0.001	-	-0.000	-
Corruption control	0.107***	-0.015	0.108***	-0.017	0.110***	-0.010	0.111***	-0.012
Political stability	0.003	0.030	-0.005	0.027	-0.011	0.030	-0.019	0.026
(A) Percentage of female board members (average 2008 to 2012)	-0.002	0.003	-0.029	-0.049	0.013	0.018	-0.011	-0.031
(B) Percentage of female loan officers (average 2008 to 2012)	0.088***	0.021	0.084***	0.034	0.075***	0.044	0.072***	0.054
(C) Percentage of female borrowers	-0.207***	0.021	-0.172***	0.010	-0.186***	0.020	-0.150***	0.012
(D) Portfolios at risk greater than 30 days	-0.545	0.389*	-0.127	-0.075	-0.563	0.347*	-0.126	-0.063
(A) * (D)	-0.461	-0.834***	-1.284	-0.287	-0.428	-0.767***	-1.290	-0.119
(B) * (D)	0.018	-0.317*	-1.059	-1.276	0.016	-0.308*	-0.698	-1.186
(C) * (D)	0.574	-0.100	0.512	-0.099	0.593	-0.065	0.802	-0.035

Note: Technical bootstrapped financial efficiency (or social efficiency) (using variable returns to scale – input (or output) oriented) is dependent variable. *, **, and *** indicate significance level of coefficients at 10%, 5% and 1%, respectively. The truncated regression analysis with bootstrapping (Simar & Wilson, 2007) results above was derived from 1000 bootstrapped iterations. Method-1 is standard interaction method, and Method-2 is the interaction method as explained in Balli and Sørensen (2013). Panel FE denotes Panel regressions with fixed effect clustered on MFI's while including time dummies respectively (robust results are printed). Hausman Test is calculated only for Panel data analysis for the null hypothesis that panel FE and panel RE have similar coefficients against the alternative hypothesis that Panel FE is favourable. We have found strong evidence to favour Panel FE for all the regressions above and printed results with Panel FE only. Constant is included but not reported to all the regressions. Non-profit-oriented and Regulated dummies are dropped from Panel FE regressions due to perfect correlations with fixed effect dummies. Year variable as a trend is included in truncated regressions but not reported.

Highlights

- This study examines the efficiency of South Asian microfinance institutions;
- Bias corrected efficiency estimates are regressed on a set of explanatory variables using double bootstrap truncated regression and panel data regression;
- First stage results suggest that institutions are more financially efficient than socially efficient;
- Second stage regression reveals that female loan officers are positive determinants of microfinance institutions' efficiency.