GENDER EFFECT ON MICROFINANCE EFFICIENCY: A ROBUST NONPARAMETRIC APPROACH

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Gender effect on microfinance efficiency: A robust nonparametric approach

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Abstract

The main objective of this study is to assess the impact of gender on microfinance social efficiency. Our methodology is based on the most recent nonparametric techniques to estimate the gender effect. We use a conditional directional free disposal hull (FDH) approach as well as its robust version of order-α; we study the effect of the heterogeneity factor on the difference of conditional and non conditional inefficiencies as well as on the inefficiency level using a local linear regression and we test the significance of its effect using a wild double bootstrap procedure. Using a cross-country sample of 680 microfinance institutes (MFIs) in 2011 from six main regions of the world, our findings suggest that gender diversity has globally a positive impact on the microfinance social efficiency. However, the nature of the effect depends on the considered heterogeneity factor and we find that the boardroom gender diversity effect is linear, whereas the effect of the percentage of women loan officers is non linear (U-shaped on the difference of inefficiencies and inverted U-shaped on the inefficiency levels). We assess the robustness of our findings on various subsamples (global or regional scale, and also depending on the considered profit oriented status). Our findings reinforce the importance of the role played by women in MFI social efficiency.

Key Words: Microfinance, Gender, Efficiency, Heterogeneity, Nonparametric Robust frontier models

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1 Introduction

Microfinance has emerged over the last three decades as a powerful tool for financial inclusion and women's empowerment, now an essential component of the financial system of many developing and emerging economies. Microfinance institutions (MFIs) are effective in fighting poverty and financial exclusion, even if some studies (Banerjee et al. (2015a), Banerjee et al. (2015b)) and tragic experiences, such as the suicides in Andhra Pradesh, have relativized the scope of the social output of microfinance. Over the past two decades, the microfinance sector has experienced some significant developments, one of which is commercialization. This trend towards commercialization has resulted in the institutional transformation of some MFIs that have moved from socially-oriented non-profit MFIs to for-profit-oriented MFIs (Fernando (2004), D'Espallier et al. (2017)). Commercialization has also allowed many MFIs to reduce their dependence on subsidies. Moving towards commercialization is therefore associated with easier access to domestic and cross-border funding, either from banking and financial markets directly, or indirectly via microfinance investment vehicles (MIVs). Since commercialization is associated with the so-called microfinance mission drift, donors and social investors might consider the social efficiency of microfinance as an essential criterion to benchmark MFIs before deciding to contribute, in other words, their ability to effectively mobilize resources to achieve the social objectives.

Several approaches have been used to assess the social impact of microfinance. These include aggregate measures, such as social ratings (Beisland et al. (2020)), field experiments and randomized control trials (Banerjee et al. (2015a), Banerjee et al. (2015b); Bulte et al. (2017); Karlan and Zinman (2010)), and parametric and nonparametric efficiency approaches. Our focus in this study is on the reliability of the nonparametric efficiency approach. The lack of robust measurement tools and controlling for heterogeneity are the main weaknesses of current studies on the efficiency of microfinance. Our methodology is based on the most recent nonparametric frontier estimation techniques to interpret the gender effect. We pay particular attention to the robustness and heterogeneity issue, and use the nonparametric conditional Free Disposal Hull (FDH) approach that Cazals et al. (2002) introduced and Daraio and Simar (2005) developed, as well as the robust version order-α (see Aragon et al. (2005)). We also consider the general directional distance approach to measure inefficiency (Chambers et al. (1996); Färe and Grosskopf (2006); Färe et al. (2008)) and test nonparametrically the impact of gender on both the frontier and the level of inefficiency (see Racine (1997) and Daraio and Simar (2014)).

A significant number of studies on microfinance efficiency have recently been carried out, mostly based on a nonparametric approach, namely data envelopment analysis (DEA) (Fall et al. (2018)). Some studies benchmark MFIs by seeking to identify the best practices (Gutiérrez-Nieto et al. (2009); Piot-Lepetit and Nzongang (2014)), others, including the most recent (Bibi et al. (2018); Fall et al. (2018); Wijesiri et al. (2015)), analyze the determinants of MFI efficiency using Simar and Wilson (2007) double bootstrap procedure, which allows drawing more robust frontiers and overcoming the serial correlation problem. However, as Simar and Wilson (2007) or Simar and Wilson (2011) emphasize, this procedure is only valid if the efficiency level is exclusively explained by factors that are under the control of managers, which is not often the case. To date, microfinance efficiency studies are likely biased and not robust, insofar as they do not control for the effect of environmental factors (heterogeneity) in the frontier estimation.

In this paper, we provide a more rigorous analysis of heterogeneity in modeling efficiency. We include two heterogeneity factors (Z_1 and Z_2) in defining the conditional frontier. Z_1 is captured by boardroom gender diversity and measured as the percentage of female board members. Z_2 is measured by the percentage of female loan officer. The boardroom gender diversity effect on firm performance and risk is unclear and inconsistent across studies (Adams and Ferreira (2009); Bennouri et al. (2018); Conyon and He (2017); Sila et al. (2016)), and mixed in the microfinance sector (Adusei (2019); Beisland et al. (2020); Bibi et al. (2018)). Finding concerning the loan officer gender effect on MFI performance is also mixed (Beck et al. (2013); van den Berg et al. (2015)). Overall, in MFI efficiency studies, gender diversity is omitted, and when it is taken into account, is considered exogenous to defining the frontier, which is very often wrong (see Simar and Wilson (2007), Simar and Wilson (2011) for more details). The main objective of this study is thus to measure the impact of boardroom diversity and loan officer gender on the social performance of MFIs. We estimate efficiencies with and without this environmental factor to assess the impact.

To the best of our knowledge, our study is the first to comprehensively and rigorously analyze the impact of gender diversity on microfinance social efficiency by applying the recent nonparametric conditional FDH estimators. Our main focus here is social efficiency, given the link generally made between women and social performance (e.g., Boehe and Cruz (2013); D'espallier et al. (2013)). We estimate social efficiency nonparametrically by considering two inputs (operational expenses and number of employees) and a social output (the percentage of women borrowers). The two inputs are summarized following an aggregation methodology detailed in Daraio and Simar (2007) and Wilson (2018) to reduce the dimensionality of the problem. First, the social efficiency is estimated unconditionally (using directional distance) and then conditionally. The comparison of these two types of social efficiencies provides an indication of the impact of the heterogeneity factor on the efficiency frontier. These estimations are computed both globally and for each region.

Our study makes several contributions to the existing literature. First, considering existing studies on gender and microfinance performance, and providing rigorous empirical evidence of the impact of boardroom gender diversity on the social efficiency frontier of microfinance, we extend previous studies that were using the "two-step approach" (Adusei (2019); Bibi et al. (2018)). Although controlling for heterogeneity is usual in econometric (for instance, Wooldridge (2010)) and stochastic frontier analyses (Mester (1997); Bos et al. (2009)), modeling heterogeneity, whether observed or unobserved, is a much more recent development in nonparametric frontier estimations. From an empirical standpoint, to the best of our knowledge, this study is the first to investigate the effect of observed heterogeneity on the frontier level by applying the most recent nonparametric conditional techniques as presented in Daraio et al. (2019). Previous microfinance efficiency studies implicitly assume that performance is determined only by factors that are under the control of the MFI. In reality, there are several environmental factors, beyond the managers' control, that may also determine the effectiveness of MFIs. These factors may be observable or unobservable, and include geographic location, legal status, and regulated status amongst others, and are likely to introduce heterogeneity in the data. Failing to control for this heterogeneity can bias the efficiency frontier estimation (Mester (1997); Berger and Humphrey (1997)).

Second, this study is one of the few to estimate the link between gender and microfinance social efficiency on a global microfinance scale. The impact here is analyzed both at the scale of each region and at the global scale. The convergence of the results, regardless of scale and region, shows their robustness, and allows drawing conclusions about this link for the microfinance industry as a whole at the international level.

Third, by estimating a more robust frontier, our study provides guidance for regulators, policymakers, and MFI managers. The analysis of efficiency has found a favorable response from microfinance practitioners, regulators, and promoters (Fall et al. (2018)). This is a means of ensuring the preservation of their social orientation in the context of accelerated MFI commercialization. For managers and regulatory authorities, the estimated efficiency scores are essential decision support tools. They help quantify efficiency gaps in the production and management of resources, identify best practices and sources of waste, and MFI benchmarking. The quality of the estimate is therefore an essential factor. Biased estimates might lead managers to take flawed decisions and policymakers to provide weak guidance (Bos et al. (2009)). This is particularly the case in the presence of heterogeneous conditions that influence the shape and position of the efficiency frontier. When this occurs, the interpretation of the efficiency scores is difficult (see, for example, Simar and Wilson (2011)), since the distance to the frontier is no longer explained solely by the quality of management, and the units are compared based on unreachable frontiers in their working environment.

Using a cross-country sample of 680 MFIs for the year 2011 from six main regions of the world, our findings suggest that gender diversity has a positive impact on the microfinance social efficiency frontier, and this result is robust whatever the scale of analysis (global or regional) or the profit-oriented status considered. However, the nature of the effect varies depending on the heterogeneity factor considered. The effect of the heterogeneity factor Z_1 (boardroom gender diversity) on the border and the levels of inefficiency is linear, unlike the effect of the heterogeneity factor Z_2 (percentage of women loan officers) which is non linear and U-shaped on the border and U-inverted shape on the inefficiency levels. Increasing the number of female loan officers thus initially increases inefficiency level, but beyond a certain threshold comprised between 40 and 60 percent of female loan officers, this inefficiency levels decrease. The results are also consistent across regions, except for the South Asian sample.

The remainder of the paper is organized as follows. Section 2 presents the research background and prior literature. Section 3 presents the methodology followed and Section 4 describes the data and the variables used. Section 5 discusses the empirical results, and Section 6 concludes. **Note that some tables and figures are gathered in a supplementary material available online.**

2 Background and prior literature

2.1 Gender and microfinance performance

The gender issue is increasingly important in the microfinance literature (Garikipati et al. (2017)). Gender borrower based studies show that targeting female borrowers is associated with better loan portfolio quality and financial performance (Abdullah and Quayes (2016); D'Espallier et al. (2017)), while women borrowers are likely to be more credit rationed (Agier and Szafarz (2013a), Agier and Szafarz (2013b); Cozarenco and Szafarz (2018)). Our first focus is on boardroom gender diversity as previously studied. For instance, Conyon and He (2017) apply a quantile regression approach on U.S. data, showing that the presence of women on the board has a positive effect on firm performance, but this effect is not constant across the performance distribution. Female directors have a significantly larger positive effect in high-performing firms relative to low-performing firms. Adams and Ferreira (2009) analyze the impact of women in the boardroom on governance in the performance of U.S. firms, showing that gender-diverse boards allocate more effort to monitoring, but finding no clear evidence on firm performance. Using French data, Bennouri et al. (2018) find evidence consistent with Adams and Ferreira (2009). Female directorship significantly increases return on assets (ROA) and return on equity (ROE), as well as decreasing Tobin's Q in French firms. Sila et al. (2016) find that greater female board representation does not necessarily mean less risk-taking behavior in U.S. non-financial firms. As for the microfinance studies, Strøm et al. (2014) find that a female chairman of the board is positively related to MFI performance. Studies using efficiency measures of performance find opposite evidence. For instance, Bibi et al. (2018) employ the double bootstrap truncated regression approach (Simar and Wilson (2007)) to analyze factors that explain variations in microfinance efficiency, including gender presence on the board of directors. They find no significant evidence indicating that boardroom gender improves MFI financial and social efficiency. Adusei (2019), using a two-stage DEA approach, find a negative relationship between board gender diversity and technical efficiency. Unlike previous studies, we assume that boardroom gender diversity affects the level of MFIs' social efficiency frontier. The board of directors is one of the most important bodies in MFI governance (Rock et al. (1998)), achieving both the monitoring and strategic mission (Jensen (1993)). Indeed, since the board of directors has a strategic role, one might expect that the higher the number of women on the board, the greater the resources dedicated to achieving social performance, especially targeting women, as in our case. MFI boards chaired by women or with a greater proportion of women will have a stronger inclination to produce social outputs, which we measure in this study as the percentage of female borrowers. From a monitoring role perspective, relying on Adams and Ferreira (2009) showing that gender-diverse boards allocate more efforts to monitoring, we could expect that the strong representation of women on the board of directors will contribute to strengthening monitoring and ensuring that managers effectively allocate resources to achieve the objectives defined by the board of directors, which may be either social or financial, or both.

The involvement of women in MFIs can also be appreciated at the operational level. The literature has investigated, for instance, how loan officer gender can impact MFI outcomes either in terms of loan repayment performance or efficiency, but the evidence is mixed. van den Berg et al. (2015) find that male loan officers are better able than female loan officers to induce borrowers to repay, while Beck et al. (2013) find the opposite. Bibi et al. (2018) find that female loan officers are a positive determinant of microfinance efficiency in Southeast Asia, while Adusei (2019) find that gender diversity (and therefore the presence of women) in MFIs hurts technical efficiency. However, the latter used the two-step procedure of Simar and Wilson (2007), which is potentially biased.

2.2 Efficiency analysis in microfinance

Efficiency estimations have been the subject of abundant studies in recent years (Fall et al. (2018)). The traditional accounting ratio method and the frontier method are the two main approaches used to analyze the efficiency of financial intermediaries (Wijesiri and Meoli (2015); Fall et al. (2018)). In the microfinance literature, the majority of studies use accounting measures of performance, specifically ratios (e.g., Cull et al. (2011), Cull et al. (2015); Galema et al. (2012)). However, more and more studies use efficiency measures derived from either using the stochastic frontier approach (SFA) (e.g., Bos and Millone (2015); Servin et al. (2012)) or classical nonparametric deterministic approach like data envelopment analysis (DEA) (e.g., Fall (2018); Piot-Lepetit and Nzongang (2014); Gutiérrez-Nieto et al. (2009)). Compared to a ratio analysis, the efficiency analysis provides more practical information in terms of management and public policy (Wijesiri et al. (2015); Fall (2018)). The recent meta-analysis of Fall et al. (2018) shows that most studies estimate an efficiency frontier with the DEA approach (over 76% of studies refer to the DEA method). The preference for a nonparametric deterministic approach is explained by its practicality and implementation simplicity. DEA, unlike SFA, requires no specification of the functional form of the production function, and is more suitable in the case of a multi-product industry such as microfinance. The downside of SFA is that due to the multiplicity of microfinance realities, it is difficult to specify a typical production function. For these reasons, scholars have generally estimated the efficiency of microfinance using DEA. However, this approach is not robust, and can lead to biased results, especially when the data contains measurement errors and in the presence of outliers or extreme values. Hence, the studies carried out to date are potentially biased due to the weaknesses inherent in the DEA method. Several scholars have developed robust nonparametric approaches based on partial frontiers (e.g., Cazals et al. (2002); Aragon et al. (2005); Daouia and Simar (2007)), but to our knowledge, such approaches have not yet been used in estimating microfinance efficiency. Therefore, we adopt the order-α robust approach for the first time to estimate microfinance efficiency.

Another particularity of current studies is their great difficulty in highlighting the impact of heterogeneity factors on the estimated efficiency frontier. In studies based on DEA, the influence of environmental factors on efficiency is highlighted by combining DEA with an econometric approach in a two-stage procedure. Early works (Segun and Anjugam (2013); Nghiem et al. (2006); Singh et al. (2013)) use a tobit model or ordinary least squares, which suffer from serial correlation according to Simar and Wilson (2007). For example, Nghiem et al. (2006) use a tobit regression in a two-step approach to analyze the determinants of microfinance efficiency in Vietnam. Singh et al. (2013) analyze the efficiency of 41 Indian MFIs also using a tobit model in a two-step approach. Segun and Anjugam (2013) use a tobit approach to analyze the determinants of the efficiency of 70 MFIs in 25 sub-Saharan African countries. More recent works (e.g., Adusei (2019); Bibi et al. (2018); Fall (2018); Wijesiri and Meoli (2015); Widiarto and Emrouznejad (2015)) use the truncated bootstrap approach of Simar and Wilson (2007), which provides more robust econometric estimates. For example, Wijesiri et al. (2015) use the two-stage double bootstrap approach of Simar and Wilson (2007) to examine technical efficiency and its determinants in 36 MFIs in Sri Lanka. Wijesiri and Meoli (2015) use the same two-stage model to estimate the productivity of 20 Kenyan MFIs between 2009 and 2012 with the DEA Malmquist productivity index. Following Simar and Wilson (2007) bootstrap truncated procedure, Fall (2018) analyzes the efficiency of microfinance institutions (MFIs) in the WAEMU area. However, these studies do not control for the effect of environmental factors on the efficiency frontier. In addition, when the scores from the first stage are biased, the results will also be biased. While the conditional frontier approaches in their robust version address this issue, to our knowledge, they have not yet been used in microfinance. In the banking literature, the only studies on efficiency frontiers that take heterogeneity into account concern stochastic frontiers (e.g., Mester (1997); Bos et al. (2009)). On the other hand, for nonparametric approaches, such as DEA and FDH, taking into account heterogeneity is almost nonexistent in the banking literature. In this paper, we suggest paving the way for their use by applying this method to a sample of MFIs.

3 Methodology

The methodology used in this paper is based on the most recent techniques on nonparametric frontier estimation and analysis of the gender effect.

For the nonparametric frontier estimation, we use the nonparametric FDH conditional approach introduced by Cazals et al. (Cazals et al. (2002)) and developed by Daraio and Simar (Daraio and Simar (2005)), as well as its robust version of order-α (introduced by Aragon et al. (2005)). We also consider the general directional distance approach to measure inefficiency (see Simar and Vanhems (2012) for an overview).

For the analysis of the gender effect, we rely on Daraio and Simar (2014) to analyze the impact of exogenous factors on the frontier itself and on the level of inefficiency. Following their methodology, we use a bootstrap approach and test from Racine (1997) to check for the significance of gender impact.

In what follows we detail each step of our analysis, from the estimation of the frontier and the level of inefficiency to the analysis of gender impact in microfinance.

3.1 Nonparametric conditional estimation

Definition of the conditional attainable set

An important literature has been devoted to the analysis of exogenous effects on the frontier estimation and the level of inefficiency. Various approaches have been proposed among which a two-stage approach which first estimate inefficiencies independently on the exogenous effect and then regress the inefficiency level on the exogenous factor. As stressed in particular by Simar and Wilson (2007) and Simar and Wilson (2011), unless the attainable set (that is the set of all combinations of inputs and outputs that are technically achievable) satisfies the restrictive assumption of 'separability', this approach is not correct and leads to wrong interpretation of the exogenous effect. It is then of crucial interest to first provide a correct definition of the attainable set by including the exogenous variable in its definition. Introducing environmental variables in the definition of the data generating process has been first analyzed in Cazals et al. (2002), and then developed in Daraio and Simar (2005). We then follow this approach and define marginal and conditional attainable sets as follows. Consider $x \in \mathbb{R}_+^p$ the vector of inputs used to produce output vector $y \in \mathbb{R}_+^q$. Then the marginal attainable set, that is the set of all combinations of (x, y) that are technically achievable, is defined as follows:

$$\Psi = \{(x, y) |\ x \text{ can produce } y\}.$$

Under the assumption of free disposability of inputs and outputs, we consider the random vector (X, Y) of inputs and outputs and define the following probability function:

$$H_{XY}(x, y) = \text{Prob}(X \leq x, Y \geq y),$$

which represents the probability of dominating a unit operating at level (x, y). Then Ψ can be interpreted as the support of the probability function H:

$$\Psi = \{(x, y) |\ H_{XY}(x, y) > 0\}.$$

A natural way to introduce exogenous variables in the production process is to consider the random vector $Z \in \mathbb{R}^r$ and the conditional probability function:

$$H_{XY|Z}(x, y|Z = z) = \text{Prob}(X \leq x, Y \geq y|Z = z).$$

The associated conditional attainable set can then be defined as the support of the conditional probability function $H_{XY|Z}$. For any value of z, we have

$$\begin{aligned} \Psi^z &= \{(x,y)|\ Z = z,\ x \text{ can produce } y\}, \\ &= \{(x,y)|\ H_{XY|Z}(x,y|Z=z) > 0\}. \end{aligned} \tag{3.1}$$

As stressed in Bădin et al. (2012), the exogenous variable Z can have an impact not only on the distribution of inefficiencies defined independently from Z but also on boundary of the attainable set itself with respect to which the inefficiencies are measured. The classical two stage approaches ignore this second effect although it is very often encountered in empirical works. Therefore, in order to avoid this pitfall, we then consider the conditional attainable set as in (3.1) to define the efficient frontier for a unit facing the value z for the exogenous factor Z.

Definition of conditional directional inefficiencies

Once the boundary of the attainable set (e.g. the efficient frontier) is defined given the inputs, the outputs and the exogenous variables, it remains to determine a measure of the distance to the frontier. Most of the empirical studies have been based on the Farell-Debreu radial oriented measures. The main idea, for the output oriented case, is to assess how much the level of outputs should increase, for a fixed value of inputs, in order to reach the efficient frontier. Similarly, for the input oriented case, one could also measure how much the level of inputs should be reduced, for a given level of outputs, to reach the boundary of the attainable set (Farrell (1957), Debreu (1951), Shephard (1970)). In this paper, we use the directional distance that generalizes both input and output oriented cases. The basic idea is to measure the distance of any firm to the efficient frontier in a given direction, which gives a great flexibility in the implementation of the method. More precisely, consider a directional vector $d_x \in \mathbb{R}^p_+$ for the inputs and $d_y \in \mathbb{R}^q_+$ for the outputs. Under the free disposability assumption, the unconditional directional distance is defined as:

$$\begin{aligned} \beta(x,y) &= \sup\{\beta > 0 | (x - \beta d_x, y + \beta d_y) \in \Psi\}, \\ &= \sup\{\beta > 0 | H_{XY}(x - \beta d_x, y + \beta d_y) > 0\}. \end{aligned}$$

An equivalent definition is provided in the conditional setting:

$$\begin{aligned} \beta(x,y|z) &= \sup\{\beta > 0 | (x - \beta d_x, y + \beta d_y) \in \Psi^Z\}, \\ &= \sup\{\beta > 0 | H_{XY|Z}(x - \beta d_x, y + \beta d_y | Z = z) > 0\}. \end{aligned}$$

In both cases, a directional distance $\beta = 0$ indicates that the point (x, y) is on the frontier and then efficient. Otherwise, $\beta > 0$ measures the distance to the frontier in the direction (d'_x, d'_y) and can be interpreted as a level of inefficiency.

The flexibility of the method comes from the possibility to choose the direction (d'_x, d'_y) to measure the distance to the frontier. Input and output oriented measures are encompassed in this general setting when some elements of the direction are fixed at zero (Daraio and Simar (2014)). Although any value could in principle be chosen for the direction vector, it is meaningful in practice to select a reference point in the data as a benchmark value. The inefficiency will then be computed with respect to this reference point. In our implementation, we chose as reference point the median of the cloud, $d_x = \text{median}(X)$ and $d_y = \text{median}(Y)$.

Robust approach

By construction, deterministic frontier modeling do not take into account for any noise and measurement error in the data and one consequence is the sensitivity of FDH and DEA estimators to outliers and extreme values. This can lead to non-smooth and unstable estimators in practice and partial frontiers have been introduced in order to correct for this drawback. The two classical robust methods are the order-m frontier method introduced by Cazals et al. (2002) and the order-α frontier method developed by Aragon et al. (2005) and Daouia and Simar (2007)). Both methods approximate the true frontier and define partial frontiers that depend on some tuning parameter (m or α). We focus here on the extension to directional distance setting (see Simar and Vanhems (2012)) of the order-α method (in order to save space, since both robust methods would give similar results). The main idea is to benchmark against the α-quantile frontier, that is the partial frontier that leaves on average $\alpha \times 100\%$ of points above the quantile frontier. The order-α directional distances (conditional and unconditional) are then defined as:

$$\begin{aligned}
\beta_\alpha(x, y) &= \sup\{\beta > 0 | H_{XY}(x - \beta d_x, y + \beta d_y) > 1 - \alpha\}, \\
\beta_\alpha(x, y|z) &= \sup\{\beta > 0 | H_{XY|Z}(x - \beta d_x, y + \beta d_y | Z = z) > 1 - \alpha\}.
\end{aligned}$$

In this setting, the coefficient β_α can be negative which indicates that the point (x, y) is above the frontier. The tuning parameter α allows to evaluate the amount of points left above the frontier and when $\alpha \to 0$, β_α converges to the full inefficiency β. Obviously, in practice, the tuning parameter needs to be chosen carefully and a discussion on this choice is provided below.

Nonparametric FDH estimation

We consider a sample of observations $(X_i, Y_i, Z_i)_{i=1,\dots n}$. In order to obtain the FDH estimator (conditional /unconditional, full or robust), we need to replace the probability function H_{XY} by its empirical counterpart and $H_{XY|Z}$ by a smooth kernel estimator (see Daraio et al. (2019) for details). We then obtain estimators for the conditional efficiency measures $\hat{\beta}(x, y|z), \hat{\beta}_\alpha(x, y|z)$ and for the non conditional measures $\hat{\beta}(x, y), \hat{\beta}_\alpha(x, y)$.

These computations require in particular the tuning of several smoothing parameters: the order α and a bandwidth parameter h for the kernel estimator of $H_{XY|Z}$. Considering the choice of α, a classical way to proceed is to use the outlier detection rule initially by Simar (2003), or as suggested by Daraio and Simar (2014), to calibrate this tuning parameter in order to leave a fixed (and small) percentage of points above the frontier. In our application, we chose α so that around 8% of points are left above the frontier. Considering the choice of the bandwidth parameter h, least square cross validation methods have been classically used (see Li and Racine (2007)). Note also that Simar et al. (2016) have proposed an efficient selection rule.

One important issue when applying nonparametric FDH methods is the curse of dimensionality: the larger the number of inputs and outputs, the slower the rate of convergence of the estimator. (see for example Wilson Wilson (2018) for a careful analysis of this problem). Among the various solutions suggested in the literature, one possibility is to aggregate inputs or outputs, as explained in Daraio and Simar (2007). We chose to aggregate our inputs and checked that the aggregated input was highly correlated with the initial ones.

3.2 Gender effect on the frontier and the level of inefficiency

Descriptive analysis

In what follows, to simplify the presentation and stick to our application, we assume that the exogenous variable Z is of dimension 1 ($r = 1$).

We evaluate the difference between the conditional inefficiency measure and the unconditional inefficiency measure as follows:

$$\begin{aligned} R(x, y|z) &= \beta(x, y|z) - \beta(x, y), \\ R_\alpha(x, y|z) &= \beta_\alpha(x, y|z) - \beta_\alpha(x, y). \end{aligned}$$

The estimated differences are denoted respectively $\hat{R}(x, y|z)$ and $\hat{R}_\alpha(x, y|z)$.

A simple analysis of the graph which represents the variation of this difference with respect to the exogenous variable Z allows to assess if the exogenous variable has a positive impact on the frontier (positive trend on average). We also analyze the difference between conditional and non conditional measures for robust frontiers. We estimate robust versions with large values of α as we expect to have some outliers in the sample. We expect that taking into account for gender in the definition of the attainable set allows to shift the frontier above and to reach higher efficient points than without the exogenous variable.

We can also analyze the effect of the exogenous variable on average efficiency scores $\beta(x, y|z)$, $\beta_\alpha(x, y|z)$. We can check whether or not the trend is positive and significant. We expect that taking into account for gender in the definition of the inefficiency measure allows to lower the inefficiency level.

Local linear regression and testing

We perform a nonparametric local linear regression of both differences of inefficiencies and inefficiencies in level on the exogenous variable Z and we test for the significance of Z. As stressed in Daraio and Simar (2014)), testing the significance of Z in the nonparametric regression of $R(X, Y|Z)$ or $\beta(X, Y|Z)$ on Z is difficult because the values of $\beta(X_i, Y_i|Z_i)$ and $\beta(X_i, Y_i)$ are not observed and have to be replaced by their nonparametric estimates. Nonparametric FDH inefficiency measures classically suffer from the curse of dimensionality and the rate of convergence depends on the number of inputs and outputs. It is also well known that naive bootstrap is generally inconsistent when estimating boundaries (see, e.g. Simar and Wilson (2000) for bootstrapping in frontier models).

These issues can be solved by considering robust partial estimators $R_\alpha(X, Y|Z)$ or $\beta_\alpha(X, Y|Z)$. Indeed, when considering fixed values for α, the limiting distribution is an usual Normal and not a distribution linked to extreme value problems. Moreover, the rates of convergence do not depend on the number of inputs and outputs. We then consider the following regressions:

$$
\begin{aligned}
\beta_\alpha(X, Y|Z) &= \mu_1(Z) + \epsilon_1, \\
R_\alpha(X, Y|Z) &= \mu_2(Z) + \epsilon_2,
\end{aligned}
$$

where $\mu_1(z) = \mathrm{E}(\beta_\alpha(X, Y|Z)|Z = z)$ and $\mu_2(z) = \mathrm{E}(R_\alpha(X, Y|Z)|Z = z)$. Following Racine (1997), we apply a bootstrap procedure to test the effect of Z on μ_1 and μ_2. The test hypothesis for the generic function μ (either μ_1 or μ_2) can be written as follows:

$$
\begin{aligned}
&H_0 : \ \forall z, \mu'(z) = 0, \quad \text{against} \\
&H_1 : \exists z, \mu'(z) \neq 0.
\end{aligned}
$$

In practice, we follow the wild double bootstrap procedure in Daraio and Simar (2014), with $B_1 = 1000$ and $B_2 = 100$ for the two bootstrap loops.

4 The data

4.1 Sample selection

The data used in this study derive from the Microfinance Information Exchange (MIX) database whose use is growing in the microfinance literature (Baquero et al. (2018); Bibi et al. (2018)). MIX is an online microfinance platform ensuring the financial transparency of MFIs, thus helping to address the key challenge they face, namely lack of reliable, comparable, and publicly available information. Currently, the MIX platform discloses information on more than 2,500 key MFIs around the world. However, using the MIX database leads to at least three issues.

The first is related to sample selection bias, which we do not control for in this study. MIX is a self-reported database and MFIs voluntarily disclose the information.

The second issue is data reliability. The MIX data are of unequal quality. Indeed, MIX uses a five-point ordinal scale (diamond scale) to classify MFIs according to their level of transparency and reliability of information. The highest diamond levels (four and five) indicate that the organization has supplied audited financial statements and/or is rated by rating agencies specialized in MFIs. To overcome the data reliability issue, we focus on MFIs with at least a three-diamond disclosure rating on MIX. Our initial sample consisted of an unbalanced panel data of 2,256 MFI-year observations, covering the period 2007 to 2015, thus including the 2007–2009 crisis. To note is that data on loan officer gender and percentage of women on the board of directors are available in the MIX database from 2007. To limit the potential impact of the crisis on the frontier estimation, we on focused MFIs with available and complete data for the year 2011. Furthermore, compared to other years, 2011 is the year for which we have the largest number of MFIs. This enabled us to build a final sample consisting of a cross-country sample of 680 MFIs for the year 2011. The final sample includes MFIs from six main regions of the world defined by MIX (Table 1): sub-Saharan Africa (95 MFIs), East Asia and the Pacific (78 MFIs), Eastern Europe and Central Asia (108 MFIs), Latin America and the Caribbean (227 MFIs), Middle East and North Africa (37 MFIs), and South Asia (135 MFIs). Our sample seems fairly evenly distributed between for-profit MFIs comprising banks, and non-bank and non-profit MFIs consisting of NGOs (Non Governmental Organizations) and cooperatives.

The third issue is the representativeness of the MIX database, which is certainly the best available worldwide database considering multiple MFI characteristics. It is, however, far from representative of the microfinance industry. Indeed, the MFI sector is comprised of hundreds of thousands of institutions all over the world. The vast majority do not report financial data to MIX. Sometimes this is simply because many MFIs are very small and have very unreliable information systems. For example, in 2014 in Ghana, only 8 MFIs reported to the MIX database. However, according to the Bank of Ghana website, there are currently 137 licensed MFIs, 31 licensed credit-only MFIs, and 12 licensed Financial NGOs. In Cameroon as of June 2017, only 42 MFIs among 531 voluntarily disclosed data to MIX. This suggests a need for caution when interpreting the results, since MFIs that report data to MIX are likely large, more profitable, and more socially performant.

4.2 Model, inputs and outputs selection

In this study, we model MFI social performance using a more robust efficiency frontier that accounts for observed heterogeneity. We assume that MFIs are production units that use a given level of inputs to facilitate the financial inclusion of economic agents excluded from the banking sector. The choice of the estimation approach is an essential question in analyzing the efficiency of organizations. There are two main approaches: the production approach and the intermediation approach (Sealey Jr and Lindley (1977)). In the production approach, the MFI is seen as a firm that provides financial products and services from capital, labor, and other associated costs. In the intermediation approach, the MFI is a firm that produces credit based on the deposits it collects. In the microfinance context, the choice of estimation approach is all the more important, as some MFIs gather or are licensed to gather deposits (shareholder MFIs and cooperatives/credit-unions), while others do not (microfinance NGOs and some non-banks financial institutions). Whether they are deposit-taking MFIs or non-deposit-taking MFIs is thus critical when choosing the estimation approach, namely the efficiency intermediation or production approach, especially as deposits are considered as an input in the former and an output in the latter. Some studies consider that estimates from models using deposits as either input or output may be biased and inconsistent, and thus develop or use two-stage DEA to account for the dual role of deposits, treating this simultaneously as an output and an intermediate input (Holod and Lewis (2011); Piot-Lepetit and Nzongang (2014)). From a financial intermediation point of view, NGOs are credit-only MFIs, and are therefore considered non-financial intermediaries insofar as they do not collect deposits. For this type of MFI, deposits do not constitute resources transformed into loans to generate profits. The intermediary approach is thus difficult to apply and may seem inappropriate for this type of MFI. We hence estimate our robust efficiency frontier using the production approach rather than the intermediation approach for several reasons. First, our sample includes MFIs with different ownership types and business models, and using the production approach allows us to compare the efficiency frontier of different institutional forms. Second, loans are the main assets of the majority of MFIs, whereas a significant number of MFIs do not collect deposits, especially NGOs and non-bank MFIs. Finally, given that the non-parametric technique requires the data to be homogeneous for all units analyzed (Dyson et al. (2001); Gutierrez-Nieto et al. (2007) and Gutiérrez-Nieto et al. (2009)), we do not include deposits as an input in our model. Since we use the production approach to evaluate and compare the efficiency of MFIs, we use physical inputs such as labor and costs, as Berger and Humphrey (Berger and Humphrey (1997)) suggest. Using physical inputs would seem appropriate for microfinance, as one of the main distinctive features of microfinance activity is that lending (credit risk analysis, credit approval, and monitoring) is highly decentralized and labor intensive (on Banking Supervision (2010); Christen et al. (2012)). This is consistent with Berger and Humphrey (1997) who recommend including physical inputs in the efficiency estimation given that they are necessary to perform transactions and process financial documents. We thus include: number of employees, which measures the number of personnel actively employed by the institution; operating expenses, including all personnel costs, depreciation, amortization, and administrative expenses expressed in US dollars. These physical inputs are widely used in prior studies on efficiency (Gutiérrez-Nieto et al. (2009); Piot-Lepetit and Nzongang (2014); Servin et al. (2012); Wijesiri and Meoli (2015) and Wijesiri et al. (2015); Fall (2018)). Since the two inputs are correlated (**corr=0.64 as shown in the correlation matrix in the supplementary material**), we aggregate both inputs (see Daraio and Simar (2007) and Wilson (2018) for an overview of dimension reduction), and obtain a unique input dimension that allows limiting the effect of this correlation in the frontier estimation. We check that the correlation between the initial inputs and the aggregated input is strong enough as well as the percentage of inertia (**see the corresponding table in the supplementary material**). According to Copestake (2007), two main indicators enable measuring the social performance of MFIs, and especially pro-poor MFIs, namely breadth of outreach (number of active borrowers) and depth of outreach (average loan size scaled by gross national income (GNI) per capita).The social performance measure we use is the breath of outreach, specifically female outreach measured by the percentage of female borrowers. This variable is often used in studies estimating social efficiency (Gutiérrez-Nieto et al. (2009); Fall (2018); Wijesiri et al. (2015); Piot-Lepetit and Nzongang (2014)). Our environmental variables are the percentage of women on the board of directors (Z_1) and the percentage of female loan officers (Z_2). As mentioned above, we first estimate an unconditional frontier without accounting for heterogeneous conditions, and then compare it with the conditional frontier to assess the gender effect on the frontier. Table 2 provides the descriptive evidence and the definition of the variables used in the study.

5 Results and discussions

As presented in Section 3, we analyze the impact of gender on social efficiency on two levels. First, we study the impact of the exogenous variable on the shape of the production set. This effect is captured by the analysis of the link between the differences of inefficiencies (conditional and non-conditional) and the environmental factor. When the link is positive and significant, it means that taking into account the environmental factor allows reaching higher levels of efficiency, and the achievable frontier is shifted upwards. Second, we study the impact of the exogenous variables (Z_1 and Z_2) on conditional managerial efficiency for a given environmental condition. This second effect is captured by the link between the conditional measure of inefficiency and the environmental factor. If the link is negative, it means that taking into account the environmental factor allows reducing the level of inefficiency. In both cases, we focus on gender effect on the robust estimators of order-α to be able to apply the double bootstrap methodology developed by Racine (1997). In all figures, from Figure 1 to Figure **??**, the value of the parameter α is set so that around 8% of units are above the unconditional frontier and the pvalue is computed from the double bootstrap procedure, as detailed in Daraio and Simar (2014). A pvalue less than 5% indicates that all derivatives of the local linear approximation with respect to the factor z are significantly different from 0 so we can interpret the shape of the local linear regression.

5.1 Main results on the full sample

We first analyze the effect of both environmental variables Z_1 and Z_2 on the full sample.

Effect of the percentage of female board members (Z_1)

Let's analyze first Figure 1(a). The points represent the values R_α of the difference between conditional and unconditional inefficiencies. The triangles represent the local linear regression of R_α on Z_1. We can see that the trend is positive but still very flat, except for large values of Z_1, above 80%. This explains why the pvalue is so large (pvalue=0.91) and the effect is not statistically significant. It can be explained by the heterogeneity of MFIs in the full sample and we expect this positive effect to become significant in the various sub-samples considered later. That would imply a positive effect of Z_1 on the conditional frontier, which corresponds precisely to an improvement of efficiency.

On Figure 1(b), we analyze the impact of Z_1 on the conditional inefficiency level β_α. The pvalue is very small (pvalue = 0.00) so we can conclude that all the derivatives with respect to z are significantly different from 0. We can then highlight a negative impact of Z_1 on MFI social inefficiency. It seems that the more the Z-factor increases, the more the level of inefficiency decreases. This negative relationship between social inefficiency and the intensity of the Z-factor means that the higher the proportion of women on the board, the lower the inefficiency of the MFI.

Thus, for the microfinance industry internationally, the presence of women on the board is salient for MFI social efficiency. These results are in line with previous studies using accounting performance measures and finding that the presence of women on the board of directors improves financial performance (Bennourri et al. Bennouri et al. (2018); Conyon and He Conyon and He (2017); Strom et al. Strøm et al. (2014)) and accounting quality (Gull et al. (2018)). Indeed, the higher the percentage of women on boards, the more likely it is that they occupy senior positions, such as in relevant board committees, that allow them to influence the strategic decisions of the board and strengthen the monitoring of the MFI CEO. In terms of social performance, the presence of women on the board is an important element of MFI effectiveness that helps reducing MFI social inefficiency. The presence of women in MFI management ensures preserving the interests of female clients in the MFI's strategy. Promoting gender in microfinance management bodies is important in the current context marked by strong commercialization and intense competition. Under pressure from private investors seeking profitability and strong competition in the sector, MFIs may neglect female clients in favor of less risky and more profitable clients. However, when women are present in management, any attempt to drift from the mission may be countered.

Effect of the percentage of female loan officers (Z_2)

By conditioning the frontier with the percentage of female loan officers (Z_2), we uncover a different relationship between Z_2 and MFIs efficiency (see Figure 2(a)) . We find a non linear U-shaped relationship between the heterogeneity factor Z_2 and the shape of the conditional production set suggesting that the conditional frontier level may decrease with the percentage of female loan officers, up to $Z_2 = 20\%$. There is a rather flat part between $Z_2 = 20\%$ and $Z_2 = 60\%$ and then the trend becomes highly positive and allows to reach a larger value for $Z_2 = 100\%$ compared to the initial value when $Z_2 = 0\%$.

On Figure 2(b), we find an inverted-U effect of Z_2 on the conditional inefficiency level. An increase of the percentage of female loan officers first increases the inefficiency level, up to $Z_2 = 40\%$, but after this threshold, the conditional inefficiency levels decrease. This inverted U-shape relationship is partly supported by the existing literature which show either opposite effects of women loan officers on loan repayment performance (Beck et al, 2013; Van den Berg et al. 2015), or a positive linear relationship between women loan officers and MFIs efficiency (Bibi et al., 2018). Our findings allow us to fuel the current debate by investigating the effect of female loan officer on MFI social output (social efficiency), especially since gender bias is likely to exist when screening female borrowers (Agier and Szafarz (2013a) and Agier and Szafarz (2013b); Brana (2013)). There is a threshold at which a larger percentage of female loan officers improves the social efficiency of MFIs. The more female loan officer are, the less important will be gender bias. Overall, there is strong convergence of the results obtained with the two considered heterogeneity factors (Z_1 and Z_2), reinforcing that women play an important role in MFI social efficiency. Our results therefore suggest that the presence of women and their influence in governance bodies (Z_1) makes it possible to drive decisions in favor of greater social efficiency and greater targeting of women. The strategic choices initiated by board gender diverse in favor of women borrowers only materialize if, at the operational level, female loan officers (Z_2) are widely represented.

5.2 Additional analysis

We check for the robustness of the gender effects and we consider various homogeneous sub-samples: breakdown by region and by MFI commercial orientation (for-profit vs. non-profit).

Gender effect according to MFIs profit-status: For-profit versus non-profit MFIs

The microfinance sector is characterized by the heterogeneity of institutional forms with some profit oriented (microfinance banks and non-bank financial institutions) and others not-for-profit oriented (non-governmental organizations [NGOs], cooperatives, and credit unions). We thus investigate whether the effect of board gender diversity (Z_1) on MFI social efficiency is consistent across these two subsamples. By conditioning the frontier by the heterogeneity factor Z_1 (percentage of female directors) findings suggest that among profit-oriented MFIs, the effect of Z_1 is positive and significant on the conditional frontier (Figure 3(a)). The presence of women on the board of for-profit MFIs enables increasing the achievable efficiency levels. However, the effect of Z1 on conditional inefficiency levels is non-significant (Figure 3(b)). In the not-for-profit sub-sample (pro-poor MFIs), the impact of Z_1 on the conditional frontier is positive and significant, although rather flat for $Z_1 \leq 40\%$ (Figure 5). The presence of women on the board of directors has a positive effect on the frontier of production possibilities. There is also a negative relationship between Z_1 and the level of social inefficiency. Increasing the proportion of women on the board reduces the ineffectiveness of non-profit MFIs.

By conditioning the border by the heterogeneity factor Z_2 (the percentage of female loan officers), for both profit oriented and nonprofit oriented MFIs sub-samples, we find a U-shape effect on the conditional frontier (Figure 4(a) and Figure 6(a)) and an inverted U-shape effect on the level of inefficiency (Figure 4(b) and Figure 6(b)).

Overall, except for the inefficiency levels conditioned by the heterogeneity factor Z_1, the results obtained are consistent across MFIs profit status, and follow similar pattern with the full sample results. One would have expected non-profit and for-profit MFIs to have different conditional social inefficiencies since the non-profit MFIs seem more geared towards targeting the poorest and the women. However, the observed similarities may indicate a change of behavior of the for-profit MFIs. The for-profit MFIs female board members are probably selected for their expertise and know-how, and therefore appear influential, since their presence seems to guide strategic choices towards a greater targeting of female borrowers. Moreover, for the for-profit MFIs, increasing the number of female loan officers allows to lower female borrowers discrimination and also to select more female loan applications. Increasing the proportion of female borrowers reduces the risk of deterioration for the MFIs loan portfolio quality and improves their yield on the loan portfolios as well as their financial performances (Abdullah and Quayes (2016)).

Gender effect across regions

We note that taking into account for Z_1 has a positive effect on the frontier for all the regions studied, although it's weaker for South Asia. The effect is also globally negative on the inefficiency level, except for South Asia. The effect is particularly strong for the Latin America and Caribbean (LAC) region. We can also note that the effect of Z_1 on the inefficiency level is a little bit weaker for the Subsaharan African region (Figures 9(b) and 10(b)). In the LAC region, microfinance has a dominant commercial profile, unlike Africa, where microfinance is more social. The influence of female managers and loan officers is naturally more noticeable in a context where the incentive to target the poor and women is weak, as in LAC, while it is less noticeable in a context where the incentive to target the poor and women is high. In African microfinance, where MFIs are more oriented towards fighting poverty, the targeting of women is almost trivialized. Donors play an important role in MFI financing in Africa, strongly encouraging MFIs to target the poor categories, particularly women. In this context, even MFIs that do not have women in management have a culture of targeting the poor and women. This is not the case when microfinance is financed by private capital, which seeks the best returns. In these contexts, which offer few incentives to target women, the presence of female managers or female loan officers can be decisive in favoring targeting women. The impact of women on social efficiency is more noticeable in MFIs with a dominant commercial profile than in those with a social orientation.

The effect of Z_2 is also globally significant for all regions except again for South Asia. The inverted U-shape phenomenon appears also when analysing the effect on the conditional inefficiency, which supports the idea of a minimal threshold value of the percentage of female loan officers to have a significant impact on the social efficiency of MFIs.

6 Conclusion

This study provides the first robust nonparametric analysis of the impact of heterogeneity on the MFI efficiency frontier. The heterogeneity factors analyzed here are the proportion of women on MFI boards (Z_1) and the percentage of female loan officers (Z_2). We pay particular attention to the robustness and heterogeneity issue, and use the nonparametric conditional FDH approach as well as its robust version of order-α. We also consider the general directional distance approach to measure inefficiency. We estimate these frontiers using a cross-country sample of 680 MFIs from six main regions of the world for Year 2011. The gender effect is analyzed by comparing unconditional and conditional inefficiency levels with respect to the heterogeneity factor and using a local linear approach. We test for the significance of gender effect using a wild double bootstrap method. Our results show that taking into account for the proportion of women on the board of directors in estimating the frontier increases the boundary of the attainable set of MFIs. The analysis of the relationship between this heterogeneity factor and the inefficiency level shows that MFI inefficiency decreases with the proportion of female board members. These effects are consistent at the regional level and between non-profit and for-profit MFIs. When considering the proportion of female loan officers as heterogeneity factor, (another indicator of the involvement of women in microfinance management), we find interesting non linear effects, a U-shape for the effect on the conditional frontier and an inverted U-shape for the effect on the inefficiency level. It means that the positive effect of social efficiency will be effective above a threshold value of at least 40% of female loan officers. Again, this effect is globally consistent among the different sub-samples.

Our analysis shows that taking heterogeneity factors into account is fundamental in estimating efficiency frontiers. This result has several implications both from a methodological and political point of view. First of all, from a methodological point of view, it seems mandatory to account for heterogeneity factors when analyzing efficiency levels. The heterogeneity factor should be included in the definition of the frontier itself and not only in a second step (unless the separability assumption holds). The robust approach of order-α allows to lower the effect of outliers in the estimation procedure and also to test for the gender effect using a bootstrap procedure. At last, performing a fully nonparametric analysis has been crucial to highlight nonlinear effects like the U-shape or inverted-U-shape effects.

From a political point of view, the positive impact of women on the level of the frontier and the level of efficiency of MFIs constitutes substantial empirical evidence for policies in favor of the promotion of gender diversity in microfinance. Our results show that an improvement in social performance can be achieved through gender diversification in MFI boards and loan officers. Our contribution takes up the challenge of controlling for observed heterogeneity.

Appendix: Tables and Figures

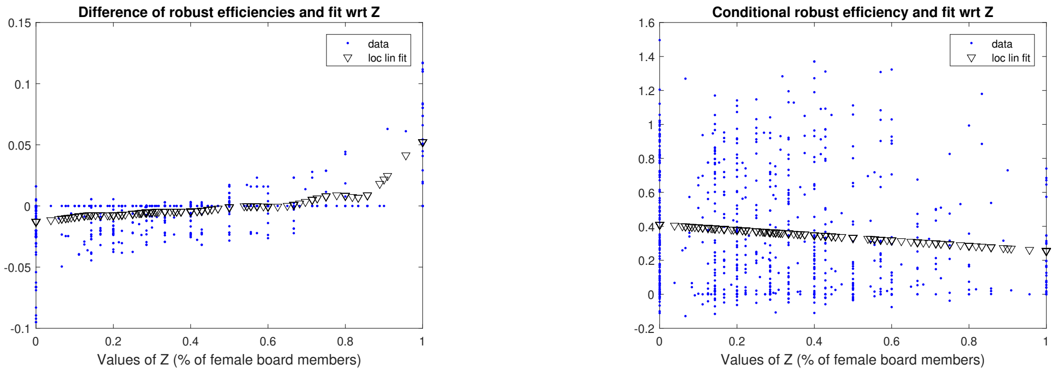
We recall that two tables (the correlation matrix and a summary of inputs aggregation) and some figures (corresponding to the regions East Asia and the Pacific, Eastern Europe and Central Asia and South Asia) are available in the supplementary material.

Region	MFIs institutional forms				
	Shareholder or for profit MFIs	**Nonprofit MFIs**		**Others**	**Total**
		Credit Unions/ Cooperatives	NGO		
Sub-Saharan Africa	37	34	23	1	95
East Asia and the Pacific	33	12	31	2	78
Eastern Europe and Central Asia	81	17	8	2	108
Latin America and The Caribbean	90	41	96		227
Middle East and North Africa	12		21	4	37
South Asia	50	7	76	2	135
Total	**303**	**111**	**255**	**11**	**680**

Table 1: MFI distribution by institutional form and region.

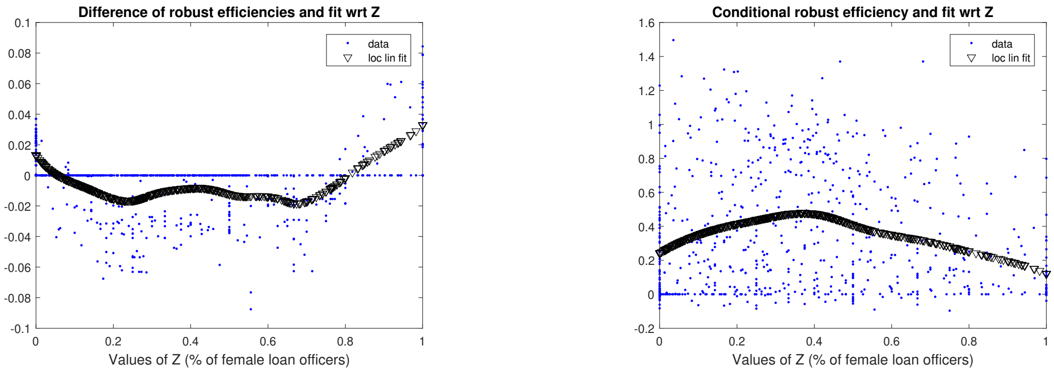
	Mean	Standard Deviation	Minimum	Maximum
Input 1: Operating expenses	6,175,979	20,085,514	681	314,492,754
Input 2: Number of employees	460	1,447	2	21,422
Output: Percent of female borrowers	65%	26%	0%	100%
Z_1: % of female board members	32%	26%	0%	100%
Z_2: % of female loan officers	38%	29%	0%	100%

Table 2: Descriptive evidence. The operating expenses include expenses not related to financial and credit loss impairment, such as personnel expenses, depreciation, amortization and administrative expenses. The number of employees corresponds to the number of individuals who are actively employed by an entity. This number includes contract employees or advisors who dedicate a substantial portion of their time to the entity, even if they are not on the entity's employee roster. The percent of female borrowers is defined by the number of active female borrowers divided number of active borrowers. Source: MIX Market



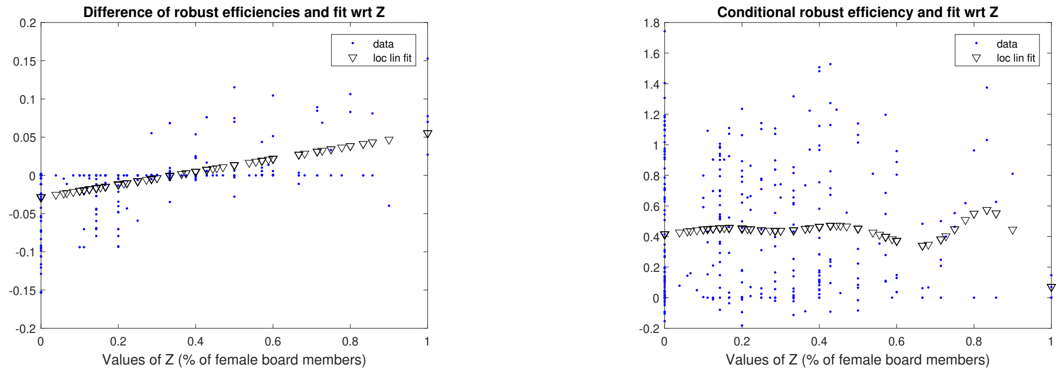
(a) $\alpha = 0.978$, pvalue $= 0.91$ (b) $\alpha = 0.978$, pvalue $= 0.00$

Figure 1: Gender effet (% of Female board members) for the full sample. Figure (a) corresponds to the nonparametric regression of R_α on Z. Figure (b) corresponds to the nonparametric regression of β_α on Z.



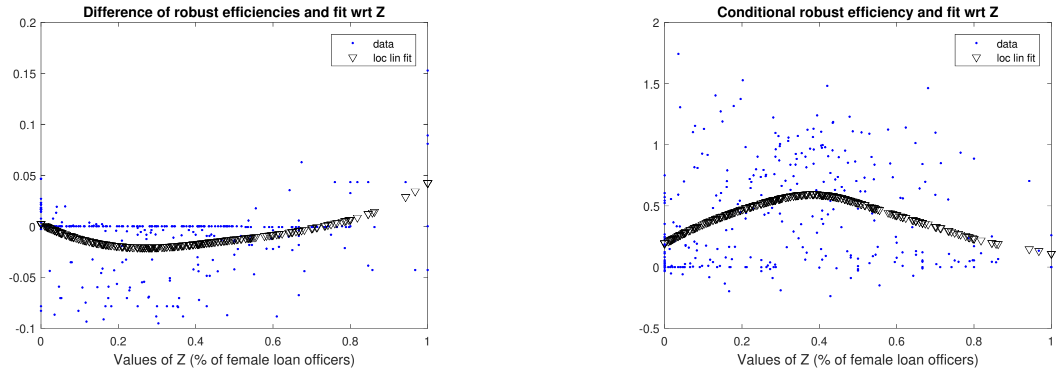
(a) $\alpha = 0.978$, pvalue $= 0.00$ (b) $\alpha = 0.978$, pvalue $= 0.00$

Figure 2: Gender effect (% of Female loan officers) for the full sample. Figure (a) corresponds to the nonparametric regression of R_α on Z. Figure (b) corresponds to the nonparametric regression of β_α on Z.



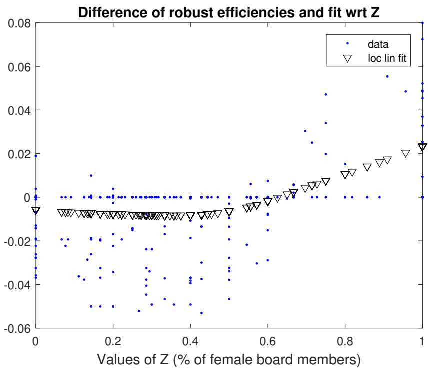
(a) $\alpha = 0.977$, pvalue $= 0.00$ (b) $\alpha = 0.977$, pvalue $= 0.12$

Figure 3: Gender effect (% of Female board members) for the 'for profit' sample. Figure (a) corresponds to the nonparametric regression of R_α on Z. Figure (b) corresponds to the nonparametric regression of β_α on Z.

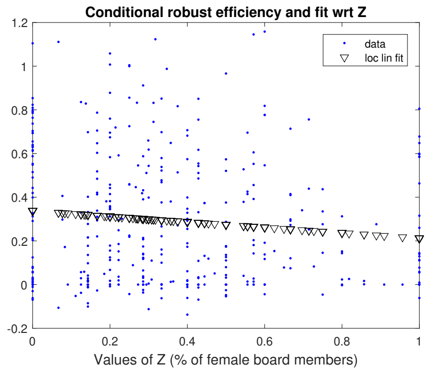


(a) $\alpha = 0.977$, pvalue $= 0.00$ (b) $\alpha = 0.977$, pvalue $= 0.00$

Figure 4: Gender effect (% of Female loan officers) for the 'for profit' sample. Figure (a) corresponds to the nonparametric regression of R_α on Z. Figure (b) corresponds to the nonparametric regression of β_α on Z.

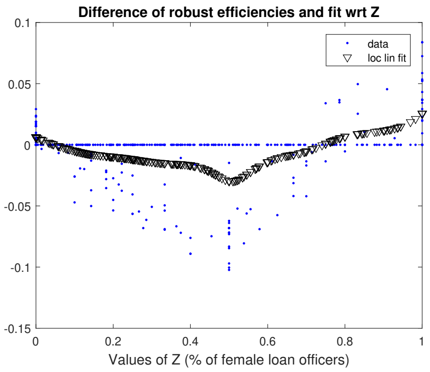


(a) α =0.97 , pvalue = 0.02

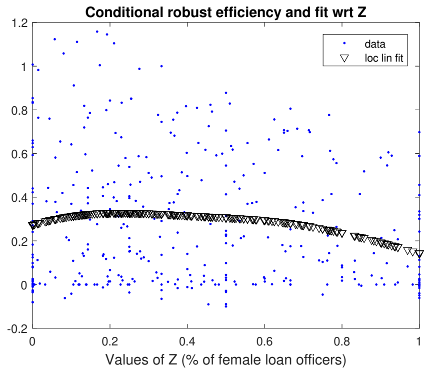


(b) α =0.97, pvalue = 0.01

Figure 5: Gender effect (% of Female board members) for the 'non profit' sample. Figure (a) corresponds to the nonparametric regression of R_α on Z. Figure (b) corresponds to the nonparametric regression of β_α on Z.

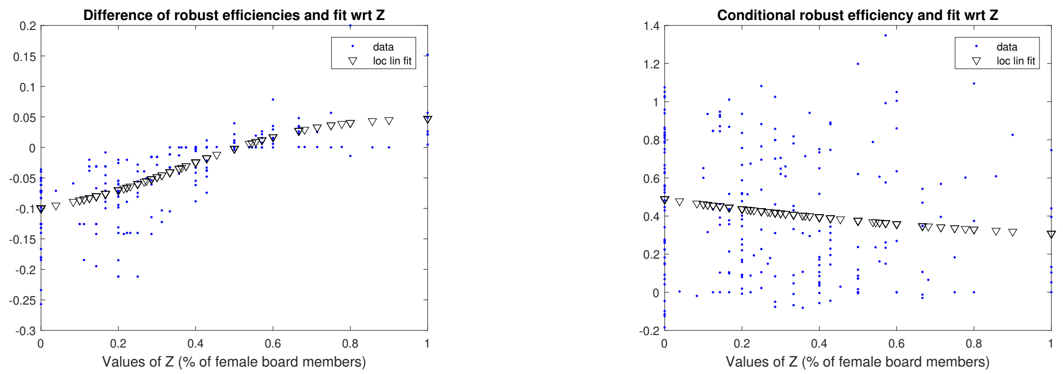


(a) $\alpha = 0.97$, pvalue = 0.00



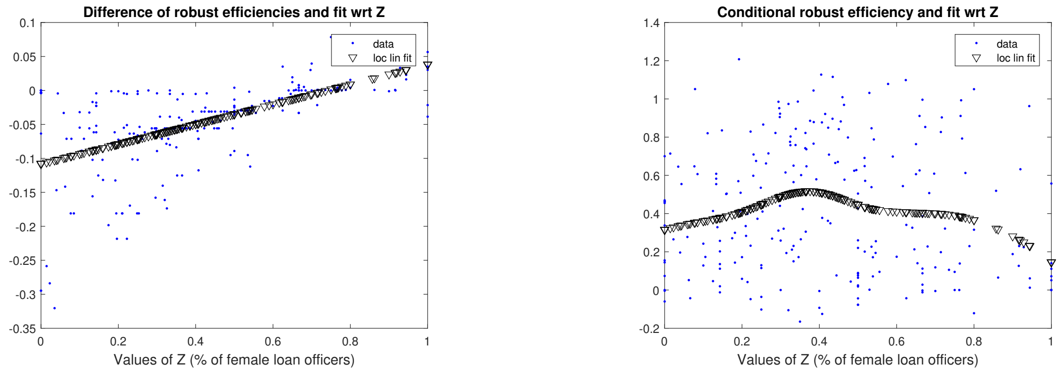
(b) $\alpha = 0.97$, pvalue = 0.02

Figure 6: Gender effect (% of Female loan officers) for the 'non profit' sample. Figure (a) corresponds to the nonparametric regression of R_α on Z. Figure (b) corresponds to the nonparametric regression of β_α on Z.



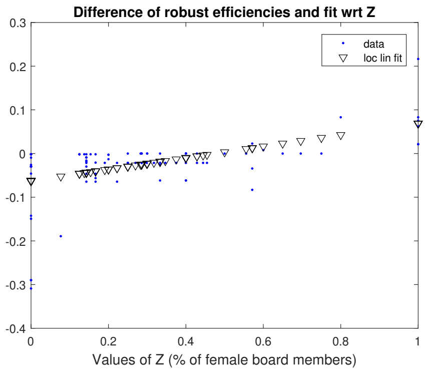
(a) α =0.98 , pvalue = 0.00 (b) α =0.98, pvalue = 0.00

Figure 7: Gender effect (% of Female board members) for the Latin America and Carribean sample. Figure (a) corresponds to the nonparametric regression of R_α on Z. Figure (b) corresponds to the nonparametric regression of β_α on Z.

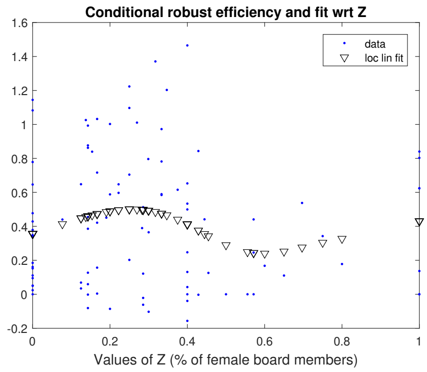


(a) $\alpha = 0.98$, pvalue = 0.00 (b) $\alpha = 0.98$, pvalue = 0.02

Figure 8: Gender effect (% of Female loan officers) for the Latin America and Carribean sample. Figure (a) corresponds to the nonparametric regression of R_α on Z. Figure (b) corresponds to the nonparametric regression of β_α on Z.

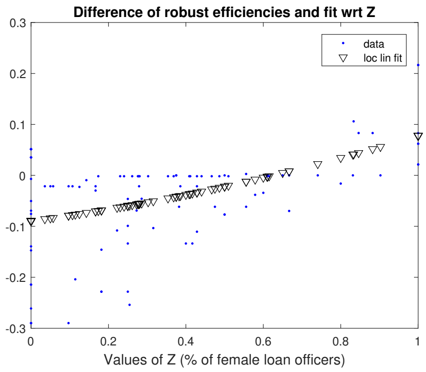


(a) $\alpha = 0.96$, pvalue $= 0.00$

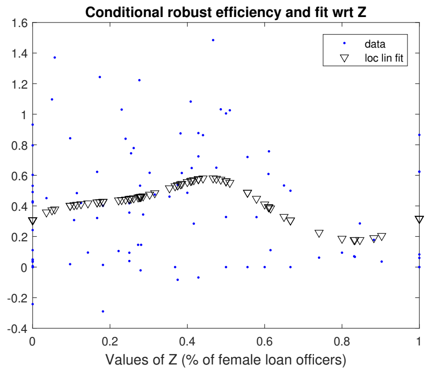


(b) $\alpha = 0.96$, pvalue $= 0.04$

Figure 9: Gender effect (% of Female board members) for the Sub-Saharan African sample. Figure (a) corresponds to the nonparametric regression of R_α on Z. Figure (b) corresponds to the nonparametric regression of β_α on Z.



(a) $\alpha = 0.96$, pvalue $= 0.00$



(b) $\alpha = 0.96$, pvalue $= 0.05$

Figure 10: Gender effect (% of Female loan officers) for the Sub-Saharan African sample. Figure (a) corresponds to the nonparametric regression of R_α on Z. Figure (b) corresponds to the nonparametric regression of β_α on Z.

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