ELSEVIER
www.elsevier.com/locate/worlddev

CrossMark

World Development Vol. 70, pp. 28–42, 2015
0305-750X/
http://dx.doi.org/10.1016/j.worlddev.2014.12.018

Practice What You Preach: Microfinance Business Models and Operational Efficiency

JAAP W.B. BOS [a] and MATTEO MILLONE [b,*]
[a] *Maastricht University School of Business and Economics, The Netherlands*
[b] *VU University Amsterdam, The Netherlands*

Summary. — The microfinance sector has room for pure for-profit microfinance institutions (MFIs), non-profit organizations, and "social" for-profit firms that aim to pursue a double bottom line. Depending on their business model, these institutions target different types of borrowers, change the size of their loans and adjust their loan pricing. We introduce a simple approach that accommodates a wide range of business models and allows us to estimate the operational efficiency of MFIs. Our empirical results show that MFIs with a high depth of outreach are most efficient, resulting in higher levels of outreach and profits for the same input mix.

Key words — microfinance, output distance function, outreach, efficiency, global

1. INTRODUCTION

At the center of the current debate about the future of microfinance, is the question whether microfinance institutions (MFIs) should be profit-oriented, privately funded, self-sustaining businesses or socially minded, subsidized, non-profit organizations (Morduch, 2000). The discussion revolves around the often-implicit disagreement regarding how MFIs can operate most efficiently, and with that the lack of consensus regarding what constitutes operational efficiency in microfinance in the first place.

Should MFIs be compared based on their profitability or based on their outreach, i.e., the extent to which they try to provide financial services to those that were previously deprived of these services? The answer to that question is important, as it helps MFIs direct efforts to improve their performance and informs (institutional) investors and donors regarding MFIs' (relative) performance.

Taken at face value, however, it appears that in the microfinance industry, there may be room for more than one business model. For-profit and non-profit firms coexist, and increasingly in the same (regional) market. The coexistence of these firms has shaped and will continue to shape the evolution of the microfinance industry.

In any market where for-profit and non-profit firms coexist, questions about fairness, efficiency, and competitiveness arise. And views differ. Whereas some argue that non-profit firms can arise endogenously in a neoclassical setting (Lakdawalla & Philipson, 2006) and may help overcome an existing market failure (Hirth, 1999), others argue against comparing for-profit and non-profit firms against the same (neoclassical) benchmark (Pauly, 1987), instead suggesting that utility maximization rather than profit maximization explains behavior in markets with mixed preferences (Lin, Dean, & Moore, 1974).

As the microfinance industry has spread across the globe, both for-profit and non-profit MFIs are faced with the same questions: what is the optimal amount of outreach, and what is a proper yield on my loan portfolio? Some non-profit institutions have proven to be more profitable than their for-profit peers, while the latter sometimes outclass their non-profit peers when it comes to outreach, suggesting that microfinance indeed accommodates not just very different business models (profit maximization, outreach maximization), but also different mixtures of these business models. What we do not yet know, of course, is which of these business models will prove to be successful in the end.

However, what we do we know is that the (non-) existence of a common benchmark is important, as benchmarks create strong incentives (Bogetoft, 1994). We also know that the notion of utility maximization is not necessarily incompatible with pure profit maximization (Kroll, Levy, & Markowitz, 1984), and that the observed choices of firms with different preferences are likely to reflect their utility functions (Smith, 1976). As Leibenstein (1966, 1978) argued and Stigler (1976) contested, firms with different preferences can have a common benchmark but show differences in performance as a result of effort discretion and non-maximizing behavior (Perelman, 2011).

In this paper, we use Leibenstein's notion of the X-inefficiency that results from not reaching that common benchmark to assess the viability of different business models in microfinance. In order to arrive at a theoretically consistent measure of X-inefficiency, we need to carefully model the production process of microfinance institutions. We develop and estimate a simple model where institutions produce an output that maximizes financial revenue (yield), an output that maximizes depth of outreach (average loan size) and an output that maximizes the breadth of outreach (the number of loans). There *can* be substitution among these outputs, which are chosen for a given a set of inputs (labor, capital). Comparing each MFI, given its mix of outputs, to a (virtual) benchmark

* We are grateful to Luis Orea, participants of the 2012 North American Productivity Workshop in Houston, the 2012 SIRP Mistra Annual Workshop in Paris, participants and discussant and the 2012 Australasian Banking and Finance Conference in Sydney, the 2013 Financial Globalisation and Sustainable Finance Conference in Cape Town, the Third European Research Conference on Microfinance in Kristiansand, and seminar participants at Maastricht University and University of Queensland for helpful comments and discussions. The usual disclaimer applies. Final revision accepted: December 18, 2014.

MFI with the same mix, we can then ask a number of important questions.

First, we ask whether and to what extent there is a trade-off between each objective (i.e., each output), assuming that all inputs have been used efficiently. At the production frontier, how much depth of outreach has to be sacrificed for a higher yield? Is it possible to combine increases in the *depth* of outreach, i.e., reducing the average loan size, with a wider *breadth* of outreach, i.e., reaching more (poor) borrowers? Our paper contributes to the literature by estimating the substitutability of outputs - related to outreach and yield - to measure these tradeoffs while controlling for existing slack in MFIs' production in either direction. Doing so is important, as we may otherwise over- or under-estimate trade-offs: think for example of an MFI that is trying to maximize outreach (depth and breadth), but does so rather inefficiently. Not accounting for that poor performance would lead to an overestimation of the trade-off between financial and social performance, since inefficient MFIs may be able to improve along both dimensions.

Second, we ask whether the operational efficiency of MFIs depends on their level of outreach. Are MFIs that serve a smaller number of richer borrowers more efficient than institutions that serve a large number of the very poor? Is it possible to efficiently offer small, but cheap loans? Our paper contributes to the literature by estimating the efficiency of MFIs in a setting that accommodates their multi-output nature. Measuring efficiency in this setting is important, as it allows both MFIs, investors and donors to benchmark institutions *given* their target market, scale, and revenue level. For example, an institutional investor wishing to invest in microfinance as part of its CSR strategy can invest in the most efficient among the MFIs that focus on outreach.

Third, and related, we ask whether differences in efficiency between MFIs with the same level of outreach depend on their social and financial orientation. We use information on the social performance profile of each MFI to answer a number of important questions. Is lending to women indeed a good way to increase outreach and how important is it to provide educational programs (Dowla & Barua, 2006; Karlan & Valdivia, 2011)? What is the nature of the risk–return relationship in microfinance (Mersland & Strøm, 2009)? What is the effect of repeated lending (Armendáriz de Aghion & Morduch, 2000)? Is it possible to efficiently serve the rural poor (Hoff & Stiglitz, 1990)? And finally, is social performance management a good idea (Copestake, 2007)? Our paper addresses these issues in a coherent framework, measuring the effects of operational changes and uncovering the different business models (for-profit, outreach maximization) that appear to explain the performance of different types of MFIs. Importantly, our analysis can help repudiate the claim that a panacea exists to "fix" microfinance: what may work for one institution may not work for another one. However, institutions with a similar output mix may be able to learn from industry best practices.

In order to answer each of these questions, we estimate a multi-output, multi-input production frontier. We use an output distance model (Cuesta & Orea, 2002), control for unobserved institutional differences using a "true fixed effects" stochastic frontier model (Greene, 2005a), and condition efficiency on a number of choice variables following Battese and Coelli (1988). We use the Microfinance Information Exchange (MIX) data, and compare 1,146 MFIs over the period from 2003 to 2010. Our analysis encompasses both strictly for-profit MFIs and firms with a social mission.

Our results show that an increase in average loan size does not only decrease depth, but also breadth of outreach, as evidenced by the negative output substitution elasticity with the number of loans. In fact, this negative relationship becomes more pronounced as the average loan size increases.

Interestingly, on average, disbursing larger loans implies a lower yield on the gross loan portfolio. Larger loans are also correlated with higher personnel and financing costs. We find support for this finding in the literature, as Mersland (2009) shows that the lower operating costs reported by for-profit MFIs are just an artifice of larger loans. As a matter of fact, we find that NGOs have lower costs per loan. According to Gutiérrez-Nieto, Serrano-Cinca, and Molinero (2007a), NGOs that rely on voluntary work have low personnel costs and thus are able to efficiently offer a large number of small loans.

In addition, we find that, contrary to Hermes, Lensink, and Meesters (2011), some MFIs can indeed combine the depth and breadth of outreach, and operate with above average levels of efficiency. However, efficiency quickly decreases as the loan portfolio becomes larger. These findings are in line with the theoretical predictions of Mersland (2009): NGOs and credit cooperatives are more efficient as they are able to lower the costs of market contracts. Such institutions are not profit maximizers and mainly operate via group loans, this makes them better equipped to cope with highly inefficient markets and asymmetric information. Roberts (2013) shows empirically that a stronger profit orientation leads to higher interest rates, but is also associated with higher costs.

Finally, we find that MFIs that specifically target the poor, lend to women and provide educational programs are more efficient. The latter finding contradicts Cull, Demirgüç-Kunt, and Murduch (2007) and Mersland and Strøm (2011) who show that MFIs that focus on lending to women are less profitable and less efficient, respectively. Repeated lending increases efficiency, whereas targeting rural markets has a negative effect on efficiency.

The remainder of this paper continues as follows. In Section 2, we review the existing literature on microfinance and the performance of MFIs. In Section 3, we introduce our analytical framework, empirical model, and estimation strategy. In Section 4, we discuss our data set. Section 5 contains our results. We conclude in Section 6.

2. BUSINESS MODELS IN MICROFINANCE

Once considered the panacea for pulling the un-bankable out of poverty, microfinance has recently come under heavy scrutiny from the public, media, and regulators. The limits of the model developed by Mohammed Yunus are not new to the academic literature. Issues of sustainability, trade-offs between social and financial goals and, more recently, efficiency have been the subject of extensive research by both academics and practitioners. The body of research on microfinance is, nevertheless, very broad in terms of objectives, methodologies, and empirical techniques. In this section, we review some of the main findings as they relate to our paper.

Morduch (1999b), in questioning the self-reported success of Grameen Bank, is among the first to challenge the notion of microfinance as a sustainable solution to poverty. When taking a closer look at the bank's financial reports, he finds that the repayment rates are not as good as they claim to be. Furthermore, he finds that, despite reporting profits, Grameen has constantly been subsidized. The findings of Morduch call into question the idea of microfinance as a profitable and yet socially oriented business.

The original view on microfinance was that MFIs following traditional banking practices would be the best at alleviating poverty. Morduch (1999a) shows that the "win–win" proposition is not realistic, both logically and empirically. Given the high costs of lending to the poor, the double bottom line proposition can be sustained only if poor borrowers strictly care about access to and not about the cost of credit (Morduch, 2000). Acknowledging that microfinance cannot be profitable and fully socially oriented at the same time is at the origin of what Morduch defines as "the microfinance schism.".

According to Robinson (2001) microfinance programs relying on subsidies and donations are limited in outreach and impact and he therefore makes a case for commercial microfinance. From that point onward, the debate on the role and the future of microfinance is dominated by two contrasting views: institutionalist and welfarist (Brau & Woller, 2004). Whereas both views assume that there is a trade-off between financial and social performance, they draw different inferences. The institutionalist view claims that in order to successfully provide financial services to the poor it is necessary to prioritize financial sustainability. The welfarist view focuses on social performance and considers the reliance on donations as necessary and justifiable, given the poverty reduction mission of MFIs.

In the literature, the trade-off between financial and social performance itself is mainly attributed to the higher costs of giving out smaller loans. Von Pischke (1996) distinguishes between demand and supply side effects. On the demand side, as the breadth of outreach increases, the probability of lending to risky borrowers increases as well, resulting in an overall riskier portfolio, with more defaults. On the supply side, smaller loans will lead to higher costs, both fixed and variable. This is a consequence of the fact that micro loans are information intensive and have high monitoring costs (Conning, 1999). Fixed costs are not a problem for sustainability as they can be lowered with economies of scale. Variable monitoring costs can be covered by charging higher interest rates, but this may worsen repayment rates. Poorer borrowers require smaller and more expensive loans that will in turn decrease profitability.

Discussions about the trade-off between financial and social performance gained momentum as a result of mission drift, i.e., the observed tendency of MFIs to move toward richer borrowers by disbursing larger loans. Copestake (2007) frames the decision in the context of a production possibility frontier, where an increase in size leads to economies of scale, allowing the MFI to focus on both depth and breadth of outreach. Since his model is dynamic, a current decrease in social performance may justify an increase in the size of an MFI in the near future. According to Ghosh and Tassel (2008), mission drift itself is the inevitable response of effective MFIs to the entry of profit-oriented investors in microfinance. Gonzalez (2010) and Mersland and Strøm (2010) show that disbursing larger loans indeed reduces operating expenses and increases profits.

Nevertheless, empirically testing the trade-off between financial and social performance poses a number of challenges. First, it is hard to distinguish between mission drift and cross-subsidization (Armendáriz & Szafarz, 2010). Second, a decrease in loan size often leads to higher interest rates. According to Mersland and Strøm (2011), "[T]he balance between outreach to the poor and financial sustainability is to a large extent a question of charging sustainable levels of interest rates since the cost of lending small amount is relatively high" (Mersland & Strøm, 2011, p. 3). They show that MFIs do not exercise monopoly power and that the high levels of interest rates are caused by increases in input prices and not by high margins. Cull *et al.* (2007) find a trade-off between the size and number of loans disbursed, and show that even if smaller loans have higher interest payments, they do not have lower repayment rates.

Meanwhile, the trade-off may depend on institutional characteristics, and can therefore differ from one MFI to the next. Mersland and Strøm (2009) look at the effects of corporate governance on the performance of MFIs. They find that most corporate governance characteristics and ownership structures have very limited or no influence on measures of outreach and financial performance. Cull and Spreng (2011) analyze the case of the privatization of the National Bank of Commerce in Tanzania. They show that even if privatization was difficult, it has led to increases in efficiency while maintaining the same level of outreach. In this particular case outreach and efficiency are not negatively related; similar results are found by Quayes (2012) for high disclosure MFIs. Finally, Louis, Seret, and Baesens (2013) use self-organizing maps and find that financial performance is positively and significantly related to social efficiency.

A number of papers look more specifically at efficiency using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Gutiérrez-Nieto, Serrano-Cinca, and Molinero (2007b) use multi-output, multi–input DEA models to measure the efficiency of MFIs, demonstrating the importance of controlling for location and NGO status. Similarly Gutiérrez-Nieto *et al.* (2007a) show the importance of social efficiency assessment. Bassem (2008) uses a sample of mediterranean MFIs to show that size has a negative impact on efficiency. Nawaz, Hudon, and Basharat (2011) confirm the result of Hassan and Sanchez (2009), showing on the one hand that MFIs with bank status specializing in individual lending tend to be financially efficient and on the other hand that unregulated NGOs are more socially efficient. Model specification is therefore critical in applications of DEA as is evident in Haq, Skully, and Pathan (2010), who show that under the production approach NGOs are more efficient while bank-microfinance institutions are the best performers under the intermediation approach. Hermes *et al.* (2011) use a stochastic frontier production model to see whether depth of outreach is related to efficiency. They find that smaller loan size leads to a decrease in efficiency.

Summing up, although we have come a long way in improving our understanding of the performance of MFIs, important questions have remained unanswered. In the presence of inefficiency, what is the trade-off between financial and social performance for inefficient MFIs? Is there a trade-off between breadth and depth of outreach? How do lending choices affect operational inefficiency, and thereby the trade-off? In order to answer these questions, we now introduce our approach to model and analyze MFIs' performance.

3. METHODOLOGY

In this section, we introduce our approach to modeling the dual objectives (profit-maximization, outreach) of MFIs. As the literature review in the previous section has shown, the potential trade-off between these objectives has been analyzed at length. Our approach differs from earlier work because we start from the premise that different institutions *can* and perhaps *should* have different output mixes, as these output mixes can result from their attempts at maximizing social and/or financial performance. In our model, an MFI is therefore not penalized for preferring one objective over the other, resulting in a different output mix. Rather, an MFI is penalized (i.e., it is inefficient) if it is less successful than other MFIs with the *same* output mix. In order to arrive at this model, we relate MFIs' preferences for social and/or financial performance to their output mix in a formal manner.

Before we introduce our empirical specification in Section (c), we therefore first revisit the notion of a trade-off between financial and social performance in microfinance. In Section (b), we then explain how we capture those trade-offs with banks' production set, consisting of a mix of outputs and inputs.

(a) *Preferences and output mixes in microfinance*

Our objective is to model the production and efficiency of firms with heterogenous preferences. We assume that all firms have access to the same technology and produce the same outputs, albeit in different proportions. Also, we assume that the transformation is (weakly) separable in outputs. We assume, therefore, that to a large extent the heterogeneity in outreach levels that is observed in the microfinance industry (Louis *et al.*, 2013) reflects MFIs' preference since the utility firms derive from a certain output set depends on these preferences.

For M inputs, N outputs, and a transformation function T that satisfies the usual conditions (Färe & Primont, 1995), we define:

$$T = \{(\mathbf{X}, \mathbf{Y}) : \mathbf{X} \in \Re^M_+, \mathbf{Y} \in \Re^N_+,\ \mathbf{X} \text{ can produce } \mathbf{Y}\}. \tag{1}$$

Now let us consider both elements in the transformation process: the output vector $\mathbf{Y}$ and the input vector $\mathbf{X}$. First, we focus on $\mathbf{Y}$. We assume that the production of an MFI is weakly separable in outputs: an MFI can choose each of its outputs, but reductions in outputs are proportional, i.e., it is not possible to reduce one of the outputs while keeping the others constant. Furthermore, we assume that within the set of possibilities allowed by the transformation function, the output mix is determined by the preferences of the MFI.

Since we are interested in comparing the efficiency of many MFIs, we can simplify our exposition by normalizing the outputs in the vector $\mathbf{Y}$, dividing each output by the maximum value taken by any of the MFIs with the same input vector $\mathbf{X}$. For the resulting scalar $\widehat{\mathbf{Y}}$, we assume that the management of an MFI i values its output mix with the following CES utility function (Dino, 2000):

$$U_i = \frac{\sum_{n=1}^{N} \theta_{n,i} \hat{y}_{n,i}^{1-\rho_i}}{1-\rho_i}, \tag{2}$$

where lower case denotes logged variables, $\sum_{n=1}^{N} \theta_{n,i} = 1$ and $\rho_i \geqslant 0$.[1] For now, we assume that each MFI produces two outputs: a high-outreach (HO) output $\hat{y}^{HO}$ and a low-outreach (LO) output $\hat{y}^{LO}$. For HO MFIs, we assume that $\theta_{HO} \geqslant \theta_{LO}$, and for LO MFIs, we assume that $\theta_{HO} < \theta_{LO}$.

In addition, we assume that $\rho^{HO} \geqslant \rho^{LO}$; whereas LO MFIs may have entered the microfinance industry because of various reasons (diversification, green washing, regulatory arbitrage, etc.), HO MFIs are assumed to have a more stringent social mission.[2]

Since the parameter ρ presents the degree of aversion against a balanced output mix, what can we learn about the utility of MFIs? To answer that question, let us start by considering HO MFIs. These MFIs are assumed to be highly averse to a balanced output mix, and will give a higher weight to the HO output in their utility function. Therefore, not surprisingly, HO MFIs strictly prefer output mixes with higher weights for $\hat{y}^{HO}$ and LO MFIs will give a higher weight to the LO output in their utility function.

Things change, however, when we consider "balanced" MFIs, who want to do well by doing good and as a result are not averse to a balanced output mix. Depending on their preferences, the preferences of their stakeholders and the extent to which the need to make a profit becomes a binding constraint, "balanced" MFIs give equal weight to the HO output and the LO output. So with what output mix do "balanced" MFIs maximize their utility? In case there is uncertainty about ρ and the output weights, the answer, as can be seen in Table 1, is not clear. Summing up, therefore, it would appear that it is much easier for both HO MFIs and LO MFIs to know when and where to exert effort in order to optimize their output mix and maximize their utility than it is for "balanced" MFIs.

In Figure 1, we show the production possibilities set for a given input mix and transformation function. Every point on the production possibilities frontier represents an efficient combination of $\hat{y}^{HO}$ and $\hat{y}^{LO}$. Any combination of $\hat{y}^{HO}$ and $\hat{y}^{LO}$ lying under the frontier is inefficient.

From Figure 1, we observe the output mixes of the three different groups of MFIs we have previously identified. HO MFIs focus on serving the poor at the low end of the market and therefore opt for a relatively high share for $\hat{y}^{HO}$. The focus of LO MFIs is on wealthier borrowers at the high end of the market and they are more likely to be accused of mission drift, since they opt for a relatively high share for $\hat{y}^{LO}$. And finally, balanced MFIs aim to do well by doing good and consequently have the most "balanced" (but perhaps not optimal) output mix.

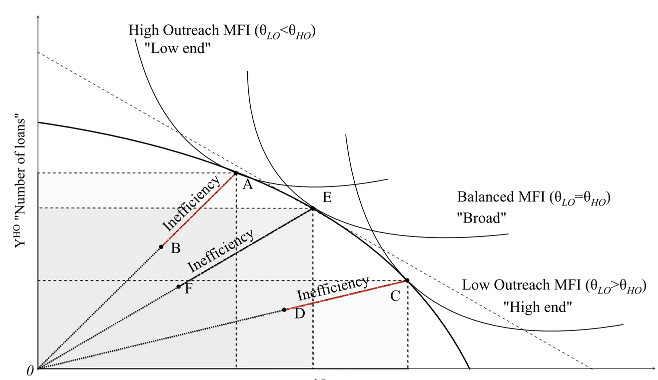

Figure 1. *Efficiency, preferences and output mixes. Notes: inefficiency of an MFI located in B is defined as $\frac{BA}{0A}$; same for MFIs located in F and D; an MFI located on the frontier is efficient.*

Table 1. *Utility, preferences and output mixes*

Type of MFI	Aversion	Preference	Utility ranking
HO MFI	$\rho > 0$	$\theta^{HO} > \theta^{LO}$	$U^{HO}\left(\tilde{\theta}^{HO} > \tilde{\theta}^{LO}\right) > U^{HO}\left(\tilde{\theta}^{HO} = \tilde{\theta}^{LO}\right) > U^{HO}\left(\tilde{\theta}^{HO} < \tilde{\theta}^{LO}\right)$
LO MFI	$\rho > 0$	$\theta^{HO} < \theta^{LO}$	$U^{LO}\left(\tilde{\theta}^{HO} > \tilde{\theta}^{LO}\right) < U^{LO}\left(\tilde{\theta}^{HO} = \tilde{\theta}^{LO}\right) < U^{LO}\left(\tilde{\theta}^{HO} < \tilde{\theta}^{LO}\right)$
"Balanced" MFIs	$\rho \geqslant 0$	$\theta^{HO} \leqslant \theta^{LO}$	$U^{LO}\left(\tilde{\theta}^{HO} > \tilde{\theta}^{LO}\right) \leqslant U^{LO}\left(\tilde{\theta}^{HO} = \tilde{\theta}^{LO}\right) \leqslant U^{LO}\left(\tilde{\theta}^{HO} < \tilde{\theta}^{LO}\right)$

Notes: θ^{LO} and θ^{HO} are the actual weights from the MFI's utility function, whereas $\tilde{\theta}^{LO}$ and $\tilde{\theta}^{HO}$ are the weights resulting from the actual output mix.

(b) *Preferences and production sets in microfinance*

The next step is to establish what constitutes this output mix. Our objective is to arrive at a set of outputs that relates to MFIs' efforts to maximize outreach and/or profits and allows us to estimate MFIs' production function in a consistent manner, allow for output substitutability. We start from the premise that total output Y for an MFI is the value added of the gross loan portfolio. We can then decompose Y as follows:

$$Y \equiv \underbrace{\frac{R_y}{1}}_{\text{Yield } (R_y)} \cdot \underbrace{\frac{GLP}{NL}}_{\text{Average loan size } (ALS)} \cdot \underbrace{\frac{NL}{1}}_{\text{Number of loans } (NL)} \tag{3}$$

where R_y is the average yield on a loan, NL is the number of loans, and ALS is the average loan size.

The decomposition in Eqn. (3) allows us to express bank (MFI) production as a function of different dimensions of outreach. Increasing the number of loans (NL), enhances the breadth of outreach, making microcredit available to a larger pool of borrowers. Lowering the average loan size (ALS) increases the depth of outreach, making microcredit affordable to poorer borrowers. Of course the affordability of microcredit also depends on its price. The higher the yield on its gross loan portfolio (R_y), the more profitable an MFI will be.

For now, let us focus on average loan size and the number of loans. On the one hand, a larger number of loans is considered as an increase in breadth of outreach.[3] On the other hand, a lower average loan size is traditionally seen as an increase in the depth of outreach (Cull *et al.*, 2007; Ghosh & Tassel, 2008; Mersland & Strøm, 2010; Hermes *et al.*, 2011; Quayes, 2012; Louis *et al.*, 2013). Of course, the latter is not perfectly correlated with the poverty level of clients, and as a result other measures such as the percentage of women borrowers have also been proposed as measures of the depth of outreach. We return to this issue later on, when we explain how we estimate and condition the efficiency of MFIs.

Obviously, MFIs can have the same gross loan portfolio, but very different mixes: one MFI may opt for a portfolio consisting of a small number of large loans, whereas another MFI may opt for a portfolio consisting of a large number of small loans.

For now, if we frame the possible trade-off between average loan size and number of loans as the choice between $\hat{y}^{LO}$ and $\hat{y}^{HO}$ in Figure 1, we first note that the shaded areas in that figure represent the size of an MFIs gross loan portfolio. In the figure, the "balanced" MFI maximizes the size of its loan portfolio. The *HO* MFI has a portfolio that is somewhat smaller, but contains more, smaller loans. The *LO* MFI also has a somewhat smaller portfolio, consisting of fewer, larger loans.

Our second, and related observation is that in comparing MFIs in the manner as displayed in Figure 1, we indeed account for the fact that they may have different preferences. If an MFI is producing at point *A* or *C*, we will consider it as efficient even if the GLP is maximized at point *E*. If fact both *A* and *C* are optimal given the shape of the utility function. If higher costs are the result of the decision to prioritize the number of loans rather than the loan size, this cannot be considered an inefficiency. Points *B* and *D* represent instead inefficient output mixes, because at each of these points one output dimension could be increased without reducing the other.

Third, since $Y = F(X)$, we note that we can rewrite Eqn. (3) as $ALS = \frac{f(X)}{R_y \cdot NL}$. It is straightforward to see that $\frac{\partial ALS}{\partial NL} = -\frac{1}{NL^2}\frac{f(X)}{R_y}$, which explains the curvature in Figure 1.[4]

Of course, in Figure 1 we compare output choices *given* an MFI's input mix. In line with the intermediation approach that has become the standard in the banking literature (Sealey & Lindley, 1977), we assume that an MFI uses three inputs: financial capital (funds), physical capital (buildings, equipment, etc.) and labor (personnel). These are measured as financial expenses (X_{fin}), administrative expenses (X_{phys}) and personnel expenses (X_{labor}), respectively.

(c) *Efficiency of microfinance institutions with heterogenous preferences and output mixes*

What remains, is the operationalization of our model for a multi-output, multi-input setting, while accounting for and measuring possible inefficiencies. In fact, we can easily build on existing models for this. To start, reconsider Eqn. (1) and let $P(\mathbf{Y})$ denote the set of feasible output vectors for an input vector $\mathbf{X}$. We can then define the distance to the frontier as:

$$D_0(\mathbf{X},\mathbf{Y}) = min.\left\{\Psi > 0 : \frac{\mathbf{Y}}{\Psi} \in P(\mathbf{X})\right\}, \tag{4}$$

where Eqn. (4) is non-decreasing, positively linearly homogeneous and convex in outputs, and decreasing in inputs. This so-called distance function takes a value of one if an output combination lies on the production frontier, otherwise its value is less than one, with $D_0(\mathbf{X},\mathbf{Y})$ if $\mathbf{Y} \in P(\mathbf{X})$.

As shown by Cuesta and Orea (2002) and others, $D_0(\mathbf{X},\mathbf{Y})$ is the inverse of the well-known output-oriented Farrell measure of operational efficiency. Therefore, an efficiency measure of one means that an MFI is fully efficient. In order to parametrize Eqn. (4), we need to impose linear homogeneity in outputs, which we can do by scaling each output by one of the outputs. If we then use a translog functional form to represent the technology, and include a series of regulation dummies (D_{legal}) to account for different types of institutions as in Hermes *et al.* (2011), we can write the output distance function as:[5]

$$\begin{aligned}-\ln(y_{it}) &= \alpha_i + \sum_{k=1}^{3}\alpha_k \ln x_{kit} + \sum_{j=1}^{2}\beta_j \ln y^*_{jit} + \frac{1}{2}\sum_{k=1}^{3}\sum_{h=1}^{3}\alpha_{kh} \\ &\quad \times \ln x_{kit}\ln x_{hit} + \frac{1}{2}\sum_{j=1}^{2}\sum_{h=1}^{2}\beta_{jh}\ln y^*_{jit}\ln y^*_{hit} \\ &\quad + \sum_{k=1}^{3}\sum_{j=1}^{2}\alpha_{kh}\ln x_{kit}\ln y^*_{hit} + \sum_{k=1}^{3}\sum_{legal=1}^{4}\zeta_{ki}D_{legal} \\ &\quad \times \ln x_{kit} + \sum_{j=1}^{2}\sum_{legal=1}^{4}\tau_{ji}D_{legal}\ln y^*_{jit} + u_{it} + v_{it},\end{aligned} \tag{5}$$

where $\ln(y_{it})$ is $\ln(ALS_{it})$ and y^*_{jit} represents $Yield_{it}$ and NL_{it}, respectively, scaled by y_{it}. The composite error term $u_{it} + v_{it}$ consists of a standard noise term, v_{it}, and an inefficiency component $u_{it} \geqslant 0$, which is assumed to be i.i.d., with a distribution truncated at $\mu, |N(\mu, \sigma_u^2)|$, and independent from the noise term.[6] Efficiency is $0 \leqslant \exp\{-u_{it}\} \leqslant 1$, where $\exp\{-u_{it}\} = 1$ implies full efficiency.

We include legal dummies interacted with inputs and outputs to capture the fact that MFIs with different legal status may face different constraints, resulting in different technologies. The direct effect is captured by firm-specific fixed effects α_{it}, measured using Greene's (Greene, 2005b) true fixed effect frontier estimator.

Following Färe and Primont (1996), the output distance function should be non-decreasing in outputs and decreasing in inputs. We can verify whether this holds, by evaluating the sum of the estimated input elasticities: [7]

$$-\sum_{k=1}^{M}\delta \ln D_0(y_{it}, x_{it})/\delta \ln x_{it}. \tag{6}$$

At the means of outputs and inputs, we expect a value significantly greater than one, indicating increasing scale economies. Likewise, to investigate the presence of trade-offs between MFIs' outputs, we evaluate:

$$\delta \ln D_0(y_{it}, x_{it})/\delta \ln y_{jt} \text{ for } i \neq j, \tag{7}$$

where a negative value indicates the existence of a trade-off.

The objective of our analysis is to benchmark MFIs' efficiency, given their output mixes and the outreach and profitability that the latter are supposed to represent. Of course, we cannot rule out the possibility that other aspects of the social and financial orientation of MFIs determine efficiency. In order to assess the importance of some of these, we follow Battese and Coelli (1988), and condition μ, the truncation point for the inefficiency distribution, as follows: [8]

$$\begin{aligned}\mu_{it} = \delta_0 &+ \delta_1 ln(\text{Risk}_{it}) + \delta_2 ln(\text{Balance}_{it}) \\ &+ \delta_3 ln(\text{Repeated-Lending}_{it}) + \delta_4 D(\text{Poor Focus}_{it}) \\ &+ \delta_5 D(\text{Rural Target}_{it}) \\ &+ \delta_6 D(\text{Social Management}_{it}) \\ &+ \delta_7 D(\text{Women Empowerment}_{it}),\end{aligned} \tag{8}$$

where Risk_{it} is the value of the portfolio at risk, measured as the product of $PAR30_{it}$ and Gross Loan Portfolio_{it}, where $PAR30_{it}$ is the percentage of the loan portfolio that has at least one more installment of the principal past due more than 30 days. We condition on risk, in order to account for the fact that performance may simply reflect risk-taking. Balance_{it} reflects the fact that at least 50% of MFIs' lending is to female borrowers, as part of their mission to support their development. It is measured as the number of female borrowers, and is intended to account for the fact that in reaching out to female borrowers, MFIs may constrain their loan portfolio choice, possibly resulting in less efficient output mixes. We condition on $\text{Repeated-Lending}_{it}$, measured as the average number of loans per borrower. As MFIs rely more on previous borrowers instead of new ones, they might reduce their outreach, but increase their efficiency by cutting screening costs.

Finally, we condition inefficiency on the different ways in which MFIs can target certain groups of borrowers, in order account for other ways in which MFIs aim to increase their outreach. $D(\text{Poor Focus}_{it})$ is a dummy variable that indicates whether an MFI targets very poor borrowers in order to increase its depth of outreach. Along the same lines, $D(\text{Rural Target}_{it})$ is a dummy variable that indicates whether the primary target market of the MFI is a rural area, attempting to serve the most remote borrowers. $D(\text{Social Management}_{it})$ is a dummy variable that indicates whether an MFI has a social performance committee. Finally, $D(\text{Women Empowerment}_{it})$, is a dummy variable that indicates whether an MFI provides educational programs targeted at the empowerment of female borrowers.

Summing up, we have now developed an empirical model that allows us to explore the trade-off between different dimensions of outreach, to benchmark the efficiency of MFIs, and to assess the factors that can improve that efficiency. In the next section, we introduce our data.

4. DATA

We use data from the Microfinance Information Exchange market. [9] The MIX dataset collects self-reported balance sheet information and is widely used in the literature (Cull, Demirgüç-Kunt, & Morduch, 2009; Ahlin, Lin, & Maio, 2011; Hermes *et al.*, 2011; Roberts, 2013). In total, MIX includes 1,146 MFIs, over the period 2003–2010. After eliminating outliers, we have an unbalanced panel with 3,880 observations. [10] Table 2 reports mean values, sorted by the legal status of the institution. [11]

The first thing to observe from Table 2, is the large heterogeneity among MFIs. On one end of the spectrum, we find banks, who are the largest institutions in the sample, offer largest loans and seem to be indifferent between lending to men or women. Despite the fact that banks on average give out large loans, they have the highest costs per borrower, suggesting that they are not able to benefit from economies of scale. Nevertheless, and consistent with their profit motive, banks have a high yield on gross loan portfolio (although it is not the highest).

At the other end of the spectrum we have rural banks, who despite their small size and small loans have low costs per borrower and a slightly lower yield. Cooperatives offer the cheapest loans but also provide some of the largest loans. Both cooperatives and non-bank financial institutions (NBFI) are relatively small in size, but NBFIs offer smaller loans, with a higher yield on their gross portfolio. NGOs are the smallest institutions. They offer the smallest loans and almost three quarters of their borrowers are women. The cost per borrower reported by NGOs is among the lowest, but at the same time the yield on gross portfolio is the highest in the sample.

Based on the descriptive statistics in Table 2, we observe that it is not obvious that there are economies of scale, since larger institutions do not report lower average costs. Also, for-profit institutions such as banks and NBFIs do not report lower total expenses or average costs, invalidating claims of superior management quality. In addition, institutions that offer larger loans tend to charge lower interest rates. For each of the outputs, standard deviations are fairly large, often larger than mean values for each of the different types of MFIs. This confirms our earlier observation that there appear to exist a multitude of business models, reflected in a large variety of output mixes, even within each category. Finally, high yields on gross portfolio seem to be unrelated to costs per borrower, but might instead be a consequence of the higher credit risk of smaller loans.

Nevertheless, these results need to be interpreted carefully for two reasons. First, low costs per borrowers reported by NGOs and Rural Banks will be influenced by subsidies, for which we have no data. Second, a significant number of institutions may be operating inside the production possibility frontier and might still be able to improve their performance in multiple dimensions.

In conclusion, the evidence reported in Table 2 shows that there are indeed strong differences in the gross loan portfolio composition, costs, and yield among MFIs. This supports the empirical specification of our model, where different MFIs are allowed to produce in different ways.

5. RESULTS

We begin this section with a brief description of the estimation of the multi-output, multi-input production frontier.

Table 2. *Descriptive statistics for different types of MFIs*

		Bank	Cooperative	NBFI	NGO	Other	Rural Bank
Outputs (Y)	Average Loan Balance/ GNI per capita	1.504	0.874	0.592	0.334	0.186	0.452
		(2.583)	(1.028)	(0.793)	(0.597)	(0.149)	(0.373)
	Number of Loans (NL)	82,410	14,874	55,231	45,378	2,909	22,264
		(114,949)	(25,089)	(119,490)	(85,012)	(2,860)	(36,220)
	Yield on gross loan portfolio % (Y_{glp})	23.020	15.512	25.858	26.756	26.240	22.3244
		(15.131)	(8.689)	(14.807)	(15.290)	(8.457)	(10.010)
Inputs (X)	Financial expenses % (FiExp/Ass)	5.719	5.277	5.797	4.842	10.270	4.985
		(3.082)	(4.887)	(3.240)	(3.104)	(0.424)	(2.621)
	Personnel expenses % (PExp/Ass)	8.410	5.422	10.187	11.293	12.180	6.666
		(4.387)	(3.321)	(6.418)	(6.864)	(6.364)	(3.165)
	Administrative expenses % (AdExp/Ass)	7.585	5.492	7.978	8.139	8.635	6.188
		(5.345)	(3.539)	(5.028)	(5.752)	(5.579)	(3.367)
Determinants (Z)	Risk %	5.026	6.405	5.053	5.559	14.840	9.813
		(7.450)	(6.534)	(6.344)	(7.438)	(3.861)	(8.606)
	Balance %	52.653	49.548	61.837	74.658	61.130	52.161
		(21.678)	(20.820)	(24.668)	(23.014)	(20.761)	(27.895)
	Multiple lending	1.068	1.064	1.056	1.050	1.000	1.058
		(0.110)	(0.203)	(0.197)	(0.250)	(0.000)	(0.134)
Costs	Cost per borrower	298.363	231.529	232.714	125.316	105.000	110.216
		(280.778)	(179.642)	(572.493)	(232.452)	(25.456)	(85.117)
	Cost per loan	283.865	219.215	221.043	113.915	105.000	106.432
		(275.757)	(170.507)	(558.364)	(127.149)	(25.456)	(84.516)
	Total expenses %	23.675	17.392	25.887	26.277	33.635	18.602
		(9.828)	(8.052)	(11.951)	(12.686)	(15.408)	(6.759)
	Number of observations	266	511	1,286	1,620	16	181

Notes: standard deviation in parentheses; all monetary values in USD, corrected for inflation. Cooperative is a cooperative or a credit union; NBFI is a non-bank financial institution; NGO is a non-governmental organization. Average loan size in USD. Yield on gross loan portfolio: one percent is 1. Inputs are scaled by assets for comparative purposes, but included non-scaled in the estimations of the output distance frontier. Portfolio at risk, 30 days late for payment. Multiple lending is defined as number of loans over number of borrowers. 3,880 observations in total.

Next, we explore the relationship between the choice of output mix, business models, and MFIs' efficiency.

(a) *Estimation results*

We start by estimating the output distance frontier. Table 9 in the Appendix contains the estimation results for our output distance frontier model, while Figure 2 shows the resulting distribution of efficiency. Importantly, we include MFI-specific fixed effects to account for firm- and country-specific conditions that may affect the production process.[12]

Before we delve into the implications of these estimation results for different groups of MFIs, a logical first question is whether efficiency matters? In Table 9, we therefore focus on λ, the ratio of inefficiency and noise. The estimated λ of 2.30993 demonstrates that there is a considerable amount of inefficiency: almost 70% of the "unexplained" variance is the result of efficiency differences.[13]

The resulting efficiency scores are portrayed in Figure 2. On average, MFIs are 82% efficient, meaning they should be able to produce 18% more outputs (given their output mix), based on what their peers operating at the frontier are able to produce, with the same input mix. Finally, we observe that efficiency is by no means normally distributed, something we have to take into account later when we do formal testing and when we calculate marginal effects.

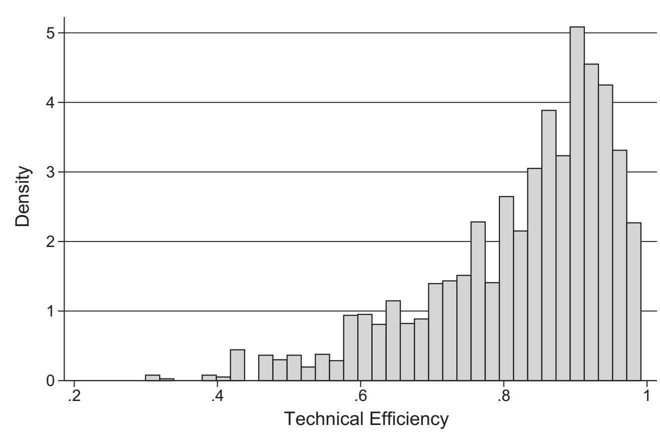

Figure 2. *Distribution of efficiency. Note: mean efficiency = 0.82; standard deviation = 0.13.*

(b) *Analysis*

Now that we have estimated the output distance frontier, we can begin our analysis of the relationship between output mixes, business models, and efficiency. We start by exploring the trade-off between financial and social performance. Next, we examine how MFIs' observed output mix is related to efficiency. Subsequently, we find out whether the level of outreach determines the trade-off between financial and social performance. Our final exploration concerns the ways in which MFIs can improve efficiency for a given output mix.

(i) *What is the trade-off between different outputs?*

Our description of the production process in Section 3 suggests that there may be a trade-off between financial and social performance. If the latter is reflected in giving many small loans to the poor, then it may for example result in higher operational costs and lower profit margins. This forces MFIs to raise interest rates resulting in more profitable, but less affordable loans. In the same vein, increasing the size of loans might allow MFIs to cut costs, attract commercial funding, and serve more borrowers in the future (Hulme *et al.*, 1996; Copestake, 2007).

Summing up, the larger the trade-off between financial and social performance is, the more it matters whether MFIs produce an output mix that is in line with their business model. And the more the trade-off varies with output levels, the higher the penalty of drifting away from that business model may be.

To find out what kind of trade-offs exist in the production process of MFIs, we calculate input and output elasticities from the estimated output distance frontier. The resulting average elasticities are reported in Table 3. From the table, we observe that both the number of loans and the yield on the gross-loan portfolio are substitutes to the average loan size. The output trade-offs in Table 3 confirm our expectations: in changing their output mix, MFIs are on average required to give up some characteristic of their current mix in order to gain in another dimension.

Table 3. *Output trade-offs and scale economies*

	Elasticity	Mean	p-Value
Y	Elasticity with respect to yield on gross loan portfolio ($\varepsilon_{Y_{GLP}}$)	−0.207	0.000
	Elasticity with respect to number of loans (ε_{NL})	−0.666	0.000
X	Elasticity to financial expenses	0.344	0.000
	Elasticity to administrative expenses	0.031	0.000
	Elasticity to personnel expenses	0.570	0.000
	Scale economies (=total input elasticity)	0.945	0.000

Notes: number of observations is 3,879; elasticities calculated as complete partial differential with respect to output, respectively input; all p-values for null hypothesis that elasticity is equal to zero, except for total input elasticity (equal to one).

Our results indicate that MFIs that target the very poor are able to do so only by charging higher interest rates, reflected in the negative elasticity of average loan size to yield on gross portfolio. Consistent with Conning (1999), depth of outreach often comes at the cost of affordability. However, as Figure 3a shows, for some MFIs the substitution elasticity of average loan size and the yield on the gross loan portfolio is either zero or positive, meaning that they are able to serve the poor without necessarily charging higher interest rates. Finally, we show that an increase in loan size always leads to a decrease in breadth of outreach, reflected in the consistently negative substitution elasticity of average loan size and number of loans in Figure 3b. If MFIs want to serve richer clients by disbursing larger loans they are able to so only by reducing the number of loans, a trade-off that becomes even stronger as loan size increases.

The fact that an increase in the number of loans is accompanied by a smaller average loan size and a higher yield for the gross loan portfolio may to some extent be explained by diseconomies of scale in production. In order to find out whether this is the case, we calculate input price elasticities in the lower half of Table 3. For our translog specification, the sum of these elasticities is a measure of MFIs' scale economies in production. Indeed, we find that on average MFIs experience scale economies that are significantly below unity, indicative of diseconomies of scale, and perhaps the result of the challenges that MFIs face when growing, such as saturated markets, less effective monitoring and lack of adequate human resources (Gonzalez-Vega, Schreiner, Meyer, Rodriguez-Meza, & Navajas, 1997).

Summing up, we find that there are significant trade-offs in the production function of MFIs. Next, we find out whether these trade-offs affect the efficiency of different business models.

(ii) *Does MFIs' outreach affect efficiency?*

Now that we have established that there are significant output mix trade-offs, we can determine whether MFIs' efficiency is affected by the breadth and depth of their outreach. To do so, and to avoid engineering our results, we adopt the same categorization provided by the MIX, and sort MFIs according to their depth and breadth of outreach, respectively.[14] First,

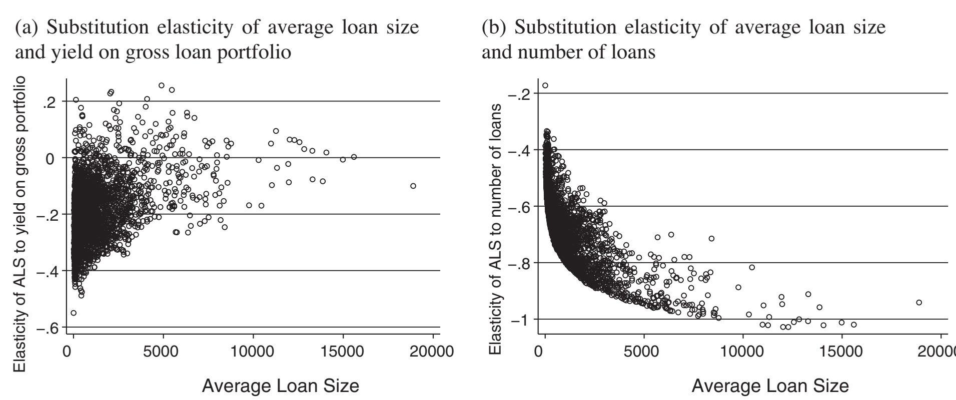

Figure 3. *Output substitution elasticities.*

Table 4. *Level of outreach and efficiency*

Breadth of outreach	N	Mean	$KW_{(S-M)}$	$KW_{(M-L)}$	$KW_{(L-S)}$	St. Dev	$F_{(S-M)}$	$F_{(M-L)}$	$F_{(L-S)}$
(a) Breadth of outreach and efficiency									
Small breadth (S)	1,732	0.837	0.344	–	–	0.103	0.000	–	–
Medium breadth (M)	1,030	0.819	–	1.000	–	0.133	–	0.000	–
Large breadth (L)	1,118	0.807	–	–	0.257	0.154	–	–	0.000

Target market	N	Mean	$KW_{(L-B)}$	$KW_{(B-H)}$	$KW_{(H-S)}$	$KW_{(S-L)}$	St.Dev	$F_{(L-B)}$	$F_{(B-H)}$	$F_{(H-S)}$	$F_{(S-L)}$
(b) Depth of outreach and efficiency											
Low end (L)	1,663	0.865	0.000	–	–	–	0.102	0.000	–	–	–
Broad (M)	1,883	0.796	–	0.000	–	–	0.135	–	0.006	–	–
High end (H)	188	0.750	–	–	0.078	–	0.153	–	–	0.283	–
Small business (S)	121	0.785	–	–	–	0.000	0.133	–	–	–	0.000

Notes: KW = Kruskal–Wallis rank test, p-values reported; $F = F$ test for the homogeneity of variances, p-values reported. Depth of outreach, represented by the target market, is measured as average loan balance per borrower/GNI per capita.

we ask whether each (depth and breadth) affects efficiency, then we study the impact of different mixes of depth and breadth of outreach on efficiency.

We start, in Table 4, with a comparison of the level and spread of efficiency for different degrees of outreach. As discussed in the previous section, the efficiency scores are not normally distributed. We therefore use a Kruskal–Wallis (KW) rank test to compare differences in levels.

Table 4a focuses on the breadth of outreach, defined as the number of active borrowers. Of course, by construction the concept of breadth of outreach is strongly correlated with the size of the institution. From the KW test statistics, we see that there is no significant difference in efficiency between MFIs with different breadth of outreach, confirming that size and efficiency are not (cor) related. Does this also imply that the ease with which an MFI reaches that average efficiency is not dependent on the breadth of outreach? In order to answer that question, we compare the spread of efficiency scores for different levels of outreach. Our results are straightforward: the higher the breadth of outreach, the more efficiency varies. MFIs that serve a smaller amount of borrowers operate more narrowly around the frontier.

In Table 4b, we repeat the analysis and look at the efficiency of MFIs with different levels of depth of outreach. Here, we measure the latter, in line with the categorization of MIX, as on average loan size over per capita Gross National Income (GNI). Importantly, the overwhelming majority of MFIs in our dataset offers loans below 149% of GNI per capita. The mean efficiency scores clearly show that MFIs that offer larger loans are significantly less efficient. The largest drop in efficiency (of 9%) is observed between low end and broad targeting. We can observe a small increase in efficiency for the limited group of MFIs that offers small business loans. We can detect a similar pattern in the spread of efficiency scores, with a large increase between low end and broad but no significant difference between high end and small business. Thus, for MFIs that focus on the very poor efficiency is not only higher but also more easily achievable.

These results have important implications for the discussion around mission drift as they do not support the claim that MFIs moving upmarket are able to increase efficiency. In fact, if increasing loan size is the response to competition with profit oriented institutions (Ghosh & Tassel, 2008), it is the wrong one. We find opposite results to Hermes *et al.* (2011), who do not take into account the multi-output nature of microfinance.

So far, then, our results show that whereas increasing the breadth of outreach does not affect the level of efficiency, increasing the depth of outreach does. Earlier, we found that there is a significant trade-off between breadth and depth of outreach. Combining both results leads to logical next question: what is the optimal mix of breadth and depth of outreach?

To answer this question, we look at the combination of depth and breadth of outreach in Table 5. From that table, we observe that the majority of MFIs no longer serve the very

Table 5. *Trade-offs in outreach and efficiency*

Target group	Breadth of outreach	N	Mean	$KW_{(S-M)}$	$KW_{(M-L)}$	$KW_{(L-S)}$	St. Dev	$F_{(S-M)}$	$F_{(M-L)}$	$F_{(L-S)}$
Low end	Small (S)	547	0.870	0.001	–	–	0.081	0.358	–	–
	Medium (M)	479	0.881	–	0.068	–	0.081	–	0.000	–
	Large (L)	637	0.849	–	–	0.348	0.128	–	–	0.000
Broad target	Small (S)	984	0.826	0.000	–	–	0.104	0.000	–	–
	Medium (M)	485	0.765	–	0.559	–	0.144	–	0.000	–
	Large (L)	414	0.764	–	–	0.000	0.168	–	–	0.000
High end	Small (S)	86	0.795	0.144	–	–	0.128	0.816	–	–
	Medium (M)	43	0.756	–	0.024	–	0.149	–	0.053	–
	Large (L)	59	0.679	–	–	0.000	0.166	–	–	0.003
Small business	Small (S)	91	0.790	0.822	–	–	0.126	0.063	–	–
	Medium (M)	22	0.781	–	0.347	–	0.166	–	0.277	–
	Large (L)	8	0.745	–	–	0.240	0.126	–	–	0.762

Notes: KW = Kruskal–Wallis rank test, p-values reported; $F = F$ test for the homogeneity of variances, p-values reported. Depth of outreach, represented by the target market, is measured as average loan balance per borrower/GNI per capita.

Table 6. *Trade-off and breadth of outreach*

Breadth of outreach	Elasticity	A. *Yield* (Y_{RGP})				B. *Number of Loans* (NL)			
		N	$\varepsilon_{Y_{RGP}}$	Mean	(KW)	N	$\varepsilon_{Y_{NL}}$	Mean	(KW)
Small breadth	Low	1,195	−0.091	0.835	(0.149)	153	−0.573	0.901***	(0.000)
	Medium	496	−0.205	0.838		472	−0.670	0.875	
	High	30	−0.265	0.882	(0.885)	1096	−0.805	0.810***	(0.000)
Medium breadth	Low	81	−0.144	0.840***	(0.002)	311	−0.569	0.902***	(0.000)
	Medium	640	−0.225	0.804		554	−0.662	0.796	
	High	304	−0.278	0.844***	(0.000)	160	−0.749	0.736***	(0.000)
Large breadth	Low	12	−0.140	0.863	(0.264)	824	−0.521	0.830***	(0.000)
	Medium	152	−0.230	0.803		262	−0.647	0.734	
	High	954	−0.321	0.808	(0.569)	32	−0.747	0.839***	(0.001)

Notes: *** signifies significant difference with middle tertile at the 1% level. Kruskal–Wallis rank test for efficiency levels.

poor, but instead supply loans to a broad(er) target market.[15] In line with previous results (Bassem, 2008), we find that for all levels of breadth of outreach, MFIs with a low-end target group are more efficient. In fact, the smallest institutions that serve the poor are still able to operate well above the mean efficiency of 82%. Almost all other MFIs offering larger loans operate below mean efficiency. The least efficient group consists of MFIs with a large number of high end clients, and includes the largest lenders in the sample. Overall, it appears that MFIs with a small to medium breadth of outreach and a high depth of outreach (i.e., serving the low end of the market) are most efficient.

A similar pattern emerges, when we consider the distribution of efficiency. MFIs that serve the poor show the lowest dispersion of efficiency around the frontier. In most cases, the spread of efficiency increases with both the average size of loans and the number of clients. Inefficiencies related to increasing loan size become more severe as MFIs start serving more borrowers. MFIs offering many large loans should do so because of economies of scale (Copestake, 2007), but appear to pay a price in terms of lower efficiency. A possible explanation is that MFIs in the last two groups (high end and small business) face more competition from traditional banks. A harsher competitive environment means a more saturated market and riskier new borrowers (Gonzalez-Vega *et al.*, 1997).

(iii) *Does MFIs' level of outreach affect the trade-off between outputs?*

In Section (a) and Figure 3, we first hypothesize and then show that output trade-offs vary depending on MFIs' business models. In this section we explore how those trade-offs vary among MFIs with different breadth and depth of outreach and whether this has any influence on efficiency. In Tables 6 and 7, we therefore compare MFIs with different levels of outreach. For each level, we compare firms with an average elasticity of output substitution to those with a high or a low elasticity.

In Table 6, we focus on breadth of outreach. From panel *A* we see that the majority of MFIs that serve a small number of clients can increase the depth of outreach without large increases in the price of the loans, in line with the low elasticities of substitution we reporter earlier. This is to be expected as small MFIs are usually non-profit organizations or in their infancy and will prefer to offer more affordable loans. Nevertheless whereas the elasticity of substitution is lowest for small MFIs, so is efficiency. When the number of clients increases, both funding constraints and competition will increase, leading to less discretion in setting prices for a given loan size. We find evidence of this as the share of MFIs operating subject to a high elasticity of substitution increases with breadth of outreach.

The story changes in panel *B*, where a high elasticity of substitution is more common for MFIs with a low breadth

Table 7. *Trade-off and depth of outreach*

Target group	Elasticity	A. *Yield* (Y_{RGP})				B. *Number of Loans* (NL)			
		N	$\varepsilon_{Y_{RGP}}$	Mean	(KW)	N	$\varepsilon_{Y_{NL}}$	Mean	(KW)
Low end	Low	360	−0.115	0.876	(0.842)	998	−0.532	0.873***	(0.000)
	Medium	540	−0.206	0.871		457	−0.653	0.863	
	High	752	−0.316	0.854	(0.430)	197	−0.764	0.829***	(0.000)
Broad	Low	777	−0.088	0.826***	(0.000)	273	−0.569	0.793	(0.419)
	Medium	645	−0.217	0.781		734	−0.667	0.794	
	High	459	−0.302	0.768	(0.377)	874	−0.798	0.799	(0.554)
High end	Low	68	−0.081	0.793**	(0.024)	5	−0.587	0.696	(0.881)
	Medium	64	−0.219	0.738		78	−0.665	0.703	
	High	55	−0.289	0.708	(0.223)	104	−0.808	0.786***	(0.000)
Small business	Low	74	−0.080	0.785	(0.568)	0			
	Medium	35	−0.214	0.792		14	−0.670	0.689	
	High	11	−0.297	0.754	(0.381)	106	−0.842	0.797***	(0.000)

Notes: **/*** signifies significant difference with middle tertile at the 5/1% level. Kruskal–Wallis rank test for efficiency levels.

of outreach. For this group, with a small loan portfolio, any increase in average loan size will result in a much larger decrease in the number of loans disbursed. As the size of the loan portfolio increases, more MFIs are able to relax the relationship between breadth and depth of outreach. As a result, the consequences of offering larger loans are worst for small MFIs who suffer a large drop in breadth of outreach. The most interesting observation from panel *B* is that very efficient MFIs are able to operate with a low elasticity of substitution between breadth and depth of outreach, implying that small MFIs are not doomed to operate within narrow boundaries but are able to considerably increase their impact through improvements in efficiency.

In Table 7, we look at how MFIs with different depths of outreach are affected by changing output trade-offs. We find that most MFIs that serve the very poor face a high trade off between depth of outreach and yield on gross loan portfolio. Offering very small loans is possible, but in most cases it appears to require charging high interest rates. Within MFIs with the same target group there is little variation in efficiency.

The relationship between our results so far and our exposition in Section 3 is clearest when we consider MFIs that target a broad group or the high end of the market. For these categories, MFIs that face the lowest elasticities of substitution, are indeed also the most efficient.

The same holds when we move to Panel *B*, where we observe that for the majority of MFIs efficiency decreases as the elasticity of substitution with the number of loans increases, mimicking the results from Table 6. Changing target group, however, does not appear to matter much in this respect.

Summing up, we see that MFIs with different business models will, to a large extent, face different trade-offs. In line with Figure 3, we find that MFIs with different mixes of breadth and depth of outreach face very different trade-offs with respect to the yield on gross portfolio. Most importantly, however, very efficient MFIs are able to relax the rigid relationship between breadth and depth of outreach, and - at least along these dimensions - can have the best of both worlds.

(iv) *Does MFIs' social orientation affect efficiency for a given output mix?*

This brings us to our final question: how does the social and financial orientation of an MFI affect efficiency for a given output mix? In order to answer that question, we assess the impact of a number of operational choices on MFIs' efficiency.

First, we consider the risk of MFIs' loan portfolio, measured as the dollar amount of the portfolio that has at least one more instalment of the principal past due more than 30 days. The amount of portfolio in default measures portfolio quality and risk attitude of the MFIs. Lenders can increase their portfolio quality by requiring collateral and engaging in more screening and monitoring. Nevertheless, MFIs usually operate in the absence of collateral, in markets where severe information asymmetry makes screening and monitoring very costly. According to Von Pischke (1996), the probability of lending to risky borrowers increases with breadth of outreach. Table 8 contains our estimation results. In the table, we report both the estimated coefficient (for inefficiency), as well as the derived average partial effect on efficiency, following Greene (2007).[16] From Table 8, we observe that increasing risk lowers efficiency.

Another way in which MFIs can rebalance their portfolios, is by changing the percentage of female borrowers. Since almost all types of MFIs on average lend more than 50% to women, rebalancing in many cases involves lowering the share of loans to women. However, the number of female borrowers is an alternative measure of depth of outreach of the MFI (Schreiner, 2002; Hermes *et al.*, 2011). From the summary statistics in Table 2, we indeed observe that NGOs and Rural Banks are similar in terms of depth of outreach, but very different when it comes to the percentage of female borrowers. Interestingly, we observe that tilting the loan portfolio even more toward female borrowers increases efficiency, in line with D'Espallier, Guérin, and Mersland (2011) who find that women are better borrowers, but contrary to the findings of Hermes *et al.* (2011).

MFIs can change the composition of their loan portfolios through repeat lending. An advantage of granting multiple loans to the same borrower, is the fact that both MFI and borrower can use the relationship they built to lower asymmetric information. A disadvantage, however, is a decrease in outreach, as fewer borrowers receive loans, ceteris paribus. Even if over-indebtedness in microfinance is a hotly debated topic (Schicks, 2010), it is a concept hard to define, let alone measure (Alam, 2012). We keep things simple, by focusing on institutions that are willing to disburse multiple loans to borrowers. Interestingly, multiple lending has a positive effect on efficiency. This is surprising at first, but consistent with the fact that it may be cheaper for MFIs to screen and monitor returning borrowers as they build a relationship.

Regardless of the size of the loans they disburse or the number of loans, MFIs that increase the depth of their outreach target the poorest clients. In line with our previous results we find that these MFIs are in fact more efficient. In similar fashion, MFIs that are truly interested in providing loans to borrowers lacking access to financial markets will focus on rural markets. Extending loans to rural borrowers is particularly costly and risky given the geographical dispersion of borrowers, lower level of income and higher reliance on agricultural production (Navajas *et al.*, 2000; Basu &

Table 8. *Operational determinants of efficiency*

Variables		*Estimation output*		*Marginal effect on efficiency*	
		Coefficient	(Std. err.)	Partial effect	(Std. err.)
Constant		-0.4529^{**}	(0.2225)		
Risk	$ln(PAR30 \cdot GrossLoanPortfolio)$	0.3133^{***}	(0.0579)	-0.0087^{***}	(0.0018)
Balance	$ln(\%Women \cdot Borrowers)$	-0.2436^{***}	(0.0724)	0.0071^{***}	(0.0015)
Multiple lending	$ln(Loans/Borrowers)$	-0.0671	(0.0682)	0.0017^{***}	(0.0004)
Poor focus	$D = 1$ *if clients poor/very poor*	-0.2204^{**}	(0.1207)	0.0057^{***}	(0.0016)
Rural target market	$D = 1$ *if target market rural*	0.2515^{**}	(0.1317)	-0.0059^{***}	(0.0016)
Social management	$D = 1$ *if SP committee exists*	-0.0121	(0.1523)	-0.0004	(0.0016)
Women empower	$D = 1$ *if education offered to women*	-0.2669^{*}	(0.1603)	0.0046^{***}	(0.0017)

Note: $^{*}/^{**}/^{***}$ signifies statistical significance at the 10/5/1% level. Marginal effects are calculated for pooled cross-section estimations.

Srivastava, 2005). Our results show that it is indeed the case as MFIs that prioritize rural borrowers are less efficient.

MFIs that truly aim to maximize outreach should be able monitor and benchmark their social performance (Copestake, Dawson, Fanning, McKay, & Wright-Revolledo, 2005). Hulme (2000) advocates for a greater focus on less rigorous internal monitoring against external assessments. We test whether the presence of a social performance committee has an effect on operational efficiency and find no significant result.

Finally, one of the main challenges faced by MFIs in lending to the poor is a low level of human capital. Lending to borrowers who are not financially literate enough can lead to a negative return on capital, high indebtedness, and low repayment rates (De Mel, McKenzie, & Woodruff, 2008). However, if the economies of scope resulting from credit officers becoming the educators of borrower are not large enough, the result can be an inefficient microfinance program (Karlan & Valdivia, 2011). Our results show that efficiency increases when MFIs offer entrepreneurship programs targeted at women.

Concluding, if MFIs want to improve efficiency without necessarily changing their output mix, they should reduce portfolio risk, explicitly target poor borrowers, increase the number of female borrowers, educate them and to a greater extent rely on longer relationships with borrowers.

6. CONCLUSION

The idea behind microfinance is quite simple: to provide financial services to the poor. In reality, its application is everything but simple. As the microfinance sector evolves, it has become an example of a sector in which firms with different business models coexist. Next to pure for-profit microfinance institutions (MFIs), the sector has room for non-profit organizations, and includes "social" for-profit firms that aim to maximize a double bottom line and do well while doing good. We introduce a benchmarking approach that accommodates different business models and allows us to estimate the efficiency of MFIs while taking into account multiple dimensions of output. Our approach allows us to benchmark institutions with different preferences without a priori selecting a performance measure that would favor the financial or the social bottom line.

Our empirical results show that there are significant trade-offs between social and financial performance in microfinance. These trade-offs do not necessarily affect all MFIs in the same manner and can be reduced by highly efficient institutions. Output mixes have a strong impact on performance as efficiency decreases when MFIs move away from their original business model, in particular when MFIs drift away from either depth or breadth of outreach. Increasing the risk of the loan portfolio and focusing on rural areas reduces efficiency while lending to and educating the very poor and women increases efficiency.

Our analysis has important consequences for researchers, investors, and practitioners. Research-wise, our results demonstrate that the inefficiencies found in the literature may to quite some extent be rational, and result from comparing MFIs to a benchmark that is not in line with their business model. For example, a non-profit MFI that is not very profitable, but maximizes its depth and breadth of outreach, will be very inefficient when assessed using a traditional banking approach, and highly efficient when subjected to an impact analysis. Our approach shows the importance of accounting for the multiple dimensions of microfinance, and underlines the power of the balanced scorecard.

For investors, our results should be food for thought. An investor whose main aim is to diversify and invest a share of her wealth in an MFI, should invest in one of the most efficient pure for-profit MFIs, in order to get the most "bang for the buck." Likewise, an NGO investing to maximize impact, should invest in an efficient non-profit MFI. Most interesting, however, is the case of the "social" investor, who wants to do well while doing good: whereas this investor may be inclined to invest in a social for-profit MFI, our results suggest that this can be suboptimal. Instead, this investor may find higher returns (both financial and non-financial), by investing part of her wealth in an efficient for-profit MFI, and the remaining part in an efficient non-profit MFI.

Finally, for MFI practitioners the implications of our results are straightforward: in the absence of major changes in output mixes (or business models), the institutions in our sample are the most efficient when doing what they do best, which turns out to be offering relatively expensive loans to the poor. Moving toward better-off clients in an attempt to reap the benefits of economies of scale, lower risk, and profit-oriented investments leads to an inefficient use of resources. Whether this is the effect of subsidies, lack of managerial skills or changing market conditions, we do not know. What we do know, is that for a given output mix, all MFIs can gain by being more selective in their lending, offering education programs and more carefully weighing the risk, background, and indebtedness of their borrowers.

In this study we investigate how MFIs with different preferences transform inputs into financial outputs. While this sheds some light on the most efficient way to provide access to finance it says very little about impact. The ability of microfinance to reduce poverty is indeed a very relevant, but very complex issue that is beyond the scope of this paper. Nevertheless, while access to credit may not be sufficient to the alleviation of poverty, we contribute to the discussion on how to efficiently use the limited resources available to the microfinance industry to satisfy the needs of the world's poor.

NOTES

1. By choosing the CES function, we assume that for each MFI $\frac{\partial U_i}{\partial y_{n,i}} > 0$ and $\frac{\partial^2 U_i}{\partial^2 y_{n,i}} < 0$.

2. In a comprehensive study, Malani, Philipson, and David (2013) investigate several reasons why non-profit firms coexist with for-profit firms. They find that evidence in favor of altruism weakly trumps evidence in favor of non-contractable quality. According to both theories, *NP* firms put less emphasis on pure profit making, in line with our assumptions made here.

3. A large body of literature has argued theoretically that smaller loans are less profitable because of higher unit costs (Von Pischke, 1996; Conning, 1999; Navajas, Schreiner, Meyer, Gonzalez-vega, & Rodriguez-meza, 2000). While this proposition finds some empirical support (Cull *et al.*, 2007; Hermes *et al.*, 2011), recent papers show MFIs are able to charge higher interest rates on smaller loans (Mersland & Strøm, 2010; Roberts, 2013; Louis *et al.*, 2013). We therefore abstain from linking profitability of the MFI to loan size, but we do take the role of loan pricing into account using the yield on the gross portfolio as an output in our analysis.

4. The same curvature is also crucial for our interpretation of inefficiency: if we take a linear combination between $\hat{y}^{NP}$ and $\hat{y}^{FP}$, then of course MFIs that are in between are inefficient. More specifically, the curvature reflects the fact that their are some limits to free disposability of outputs, and as a result such a linear combination is not (always) feasible (Bogetoft & Wang, 2005).

5. To correct for spurious interaction terms, all variables in the translog have been transformed following the Frisch-Waugh theorem.

6. In estimating Eqn. (4), we identify the components of the composite error term by re-parameterizing λ in a maximum likelihood procedure, where $\lambda(=\sigma_u/\sigma_v)$ is the ratio of the standard deviation of efficiency over the standard deviation of the noise term, and $\sigma(=(\sigma_u^2+\sigma_v^2)^{1/2})$ is the composite standard deviation. The frontier can be identified by the λ for which the log likelihood is maximized (see Kumbhakar & Lovell, 2000).

7. We add the minus sign for the dependent variable in line with Eqn. (4).

8. To control for possible multicollinearity, the variables that explain μ have been orthogonalized.

9. For more information, see: www.mix.org.

10. We exclude the top and bottom percentiles. Only the single observation is dropped as the quality of reporting usually improves with time for most MFIs. This results in 99% of our sample having at least three diamonds.

11. MIX contains MFIs from 101 countries. We control for country effects through firm-specific fixed effects.

12. These fixed effects are not included in Table 9, but available upon request from the authors. Because of the nature of the translog model, interpreting individual coefficients is notoriously cumbersome. Instead we report input and output elasticities in Table 3 and discuss them in the next subsection.

13. Since $\lambda=\sigma_u/\sigma_v$, a λ of 2.30993 means that $\sigma_u/(\sigma_u+\sigma_v)=0.6978$.

14. Depth of outreach is defined as target market by the MIX, the two terms will be used interchangeably. Definition of groups can be found in Table 10.

15. As yet, however, only a few MFIs serve small businesses.

16. Note that the latter can be significant even when the former is not, implying that very high and/or low values of the conditioning variable do not have a significant effect.

REFERENCES

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

Alam, S. M. (2012). *Does microcredit creat over-indebtedness?* Working paper. Bangladesh: Institute of Microfinance (InM).

Armendáriz, B., & Szafarz, A. (2010). On mission drift in microfinance institutions. In B. Armendáriz, & M. Labie (Eds.). *The Handbook of Microfinance* (vol. 32, pp. 341–366). Singapore: World Scientific Publishing.

Armendáriz de Aghion, B., & Morduch, J. (2000). Microfinance beyond group lending. *Economics of Transition, 8*(2), 401–420.

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

Basu, P. & Srivastava, P. (2005). *Scaling-up microfinance for india's rural poor*. World Bank Policy Research Working Papers.

Battese, G. E., & Coelli, T. J. (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics, 38*(3), 387–399.

Bogetoft, P. (1994). Incentive efficient production frontiers: An agency perspective on dea. *Management Science, 40*(8), 959–968.

Bogetoft, P., & Wang, D. (2005). Estimating the potential gains from mergers. *Journal of Productivity Analysis, 23*(2), 145–171.

Brau, J. C., & Woller, G. M. (2004). Microfinance: A comprehensive review of the existing literature. *Journal of Entrepreneurial Finance and Business Ventures, 9*(1), 1–26.

Conning, J. (1999). Outreach, sustainability and leverage in monitored and peer-monitored lending. *Journal of Development Economics, 60*(1), 51–77.

Copestake, J. (2007). Mainstreaming microfinance: Social performance management or mission drift?. *World Development, 35*(10), 1721–1738.

Copestake, J., Dawson, P., Fanning, J.-P., McKay, A., & Wright-Revolledo, K. (2005). Monitoring the diversity of the poverty outreach and impact of microfinance: A comparison of methods using data from peru. *Development Policy Review, 23*(6), 703–723.

Cuesta, R. A., & Orea, L. (2002). Mergers and technical efficiency in spanish savings banks: A stochastic distance function approach. *Journal of Banking & Finance, 26*(12), 2231–2247.

Cull, R., Demirgüç-Kunt, A., & Morduch, J. (2009). Microfinance meets the market. *The Journal of Economic Perspectives, 23*(1), 167–192.

Cull, R., Demirgüç-Kunt, A., & Murduch, J. (2007). Financial performance and outreach: A global analysis of leading microbanks. *The Economic Journal, 117*, F107–F133.

Cull, R., & Spreng, C. P. (2011). Pursuing efficiency while maintaining outreach: Bank privatization in tanzania. *Journal of Development Economics, 94*(2), 254–261.

De Mel, S., McKenzie, D., & Woodruff, C. (2008). Returns to capital in microenterprises: Evidence from a field experiment. *The Quarterly Journal of Economics, 123*(4), 1329–1372.

D'Espallier, B., Guérin, I., & Mersland, R. (2011). Women and repayment in microfinance: A global analysis. *World Development, 39*(5), 758–772.

Dino, R. (2000). *A utility-frontier production function approach for the efficiency measurement of multi-output public and non-profit organisations*. Universitá Ca' Foscari di Venezia Working Paper 2000.08.

Dowla, A., & Barua, D. (2006). *The poor always pay back: The Grameen II story*. West Hartford, CT: Kumarian Press.

Färe, R., & Primont, D. (1995). *Multi-output production and duality: Theory and applications*. Boston: Kluwer Academic Publishers.

Färe, R., & Primont, D. (1996). The opportunity cost of duality. *Journal of Productivity Analysis, 7*, 213–224.

Ghosh, S., & Tassel, E.V. (2008). *A model of mission drift in microfinance institutions*. Working Papers 08003, Department of Economics, College of Business, Florida Atlantic University.

Gonzalez, A. (2010). Microfinance synergies and trade-offs: Social versus financial performance outcomes in 2008. MIX Data Brief, 7.

Gonzalez-Vega, C., Schreiner, M., Meyer, R. L., Rodriguez-Meza, J., & Navajas, S. (1997). Bancosol: The challenge of growth for microfinance organizations. *Microfinance for the Poor*, 129–170.

Greene, W. (2005a). Fixed and random effects in stochastic frontier models. *Journal of Productivity Analysis, 23*, 7–32. http://dx.doi.org/10.1007/s11123-004-8545-1.

Greene, W. (2005b). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics, 126*(2), 269–303.

Greene, W. (2007). *Limdep econometric modeling guide* (Vol. 2). Castle Hill, Australia: Econometric Software.

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

Gutiérrez-Nieto, B., Serrano-Cinca, C., & Molinero, C. M. (2007b). Social efficiency in microfinance institutions. *Journal of the Operational Research Society, 60*(1), 104–119.

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

Hassan, M. K. and Sanchez, B. (2009). *Efficiency analysis of microfinance institutions in developing countries*. Networks Financial Institute at Indiana State University Working Paper, 12.
Hermes, N., Lensink, R., & Meesters, A. (2011). Outreach and efficiency of microfinance institutions. *World Development, 39*(6), 938–948.
Hirth, R. A. (1999). Consumer information and competition between nonprofit and for-profit nursing homes. *Journal of Health Economics, 18*(2), 219–240.
Hoff, K., & Stiglitz, J. E. (1990). Introduction: Imperfect information and rural credit markets: Puzzles and policy perspectives. *The world bank economic review*, 235–250.
Hulme, D. (2000). Impact assessment methodologies for microfinance: Theory, experience and better practice. *World Development, 28*(1), 79–98.
Hulme, D., Mosley, P., *et al.* (1996). *Finance against poverty* (Vol. 1). Routledge.
Karlan, D., & Valdivia, M. (2011). Teaching entrepreneurship: Impact of business training on microfinance clients and institutions. *Review of Economics and Statistics, 93*(2), 510–527.
Kodde, D. A., & Palm, F. C. (1986). Wald criteria for jointly testing equality and inequality restrictions. *Econometrica, 54*, 1243–1248.
Kroll, Y., Levy, H., & Markowitz, H. M. (1984). Mean–variance versus direct utility maximization. *The Journal of Finance, 39*(1), 47–61.
Kumbhakar, S. C., & Lovell, C. A. K. (2000). *Stochastic frontier analysis*. Cambridge University Press.
Lakdawalla, D., & Philipson, T. (2006). The nonprofit sector and industry performance. *Journal of Public Economics, 90*(89), 1681–1698.
Leibenstein, H. (1966). Allocative efficiency vs. x-efficiency. *The American Economic Review, 56*(3), 392–415.
Leibenstein, H. (1978). X-inefficiency xists: Reply to an xorcist. *The American Economic Review, 68*(1), 203–211.
Lin, W., Dean, G. W., & Moore, C. V. (1974). An empirical test of utility vs. profit maximization in agricultural production. *American Journal of Agricultural Economics, 56*(3), 497–508.
Louis, P., Seret, A., & Baesens, B. (2013). Financial efficiency and social impact of microfinance institutions using self-organizing maps. *World Development, 46*, 197–210.
Malani, A., Philipson, T., & David, G. (2003). Theories of firm behavior in the nonprofit sector. a synthesis and empirical evaluation. In *The Governance of Not-for-Profit Organizations*, NBER Chapters, pages 181–216. National Bureau of Economic Research, Inc.
Mersland, R. (2009). The cost of ownership in microfinance organizations. *World Development, 37*(2), 469–478.
Mersland, R., & Strøm, R. Ø. (2009). Performance and governance in microfinance institutions. *Journal of Banking & Finance, 33*(4), 662–669.
Mersland, R., & Strøm, R. Ø. (2010). Microfinance mission drift?. *World Development, 38*(1), 28–36.
Mersland, R. and Strøm, R. Ø. (2011). What drives the microfinance lending rate? Working Paper.
Morduch, J. (1999a). The microfinance promise. *Journal of Economic Literature, 37*(4), 1569–1614.
Morduch, J. (1999b). The role of subsidies in microfinance: evidence from the grameen bank. *Journal of Development Economics, 60*(1), 229–248.
Morduch, J. (2000). The microfinance schism. *World Development, 28*(4), 617–629.
Navajas, S., Schreiner, M., Meyer, R. L., Gonzalez-vega, C., & Rodriguez-meza, J. (2000). Microcredit and the poorest of the poor: Theory and evidence from bolivia. *World Development, 28*(2), 333–346.
Nawaz, A., Hudon, M., and Basharat, B. (2011). Does efficiency lead to lower interest rates? a new perspective from microfinance. Technical report, Second European Research Conference in Microfinance, Groningen, The Netherlands.
Pauly, M. V. (1987). Nonprofit firms in medical markets. *The American Economic Review, 77*(2), 257–262.
Perelman, M. (2011). Retrospectives: X-efficiency. *The Journal of Economic Perspectives, 25*(4), 211–222.
Quayes, S. (2012). Depth of outreach and financial sustainability of microfinance institutions. *Applied Economics, 44*(26), 3421–3433.
Roberts, P. W. (2013). The profit orientation of microfinance institutions and effective interest rates. *World Development, 41*, 120–131.
Robinson, M. S. (2001). *The microfinance revolution: sustainable finance for the poor* (vol. 1). World Bank Publications.
Schicks, J. (2010). Microfinance over-indebtedness: Understanding its drivers and challenging the common myths. Working Papers CEB 10-048, ULB – Université Libre de Bruxelles.
Schreiner, M. (2002). Aspects of outreach: a framework for discussion of the social benefits of microfinance. *Journal of International Development, 14*(5), 591–603.
Sealey, C. W. J., & Lindley, J. T. (1977). Inputs, outputs, and a theory of production and cost at depository financial institutions. *The Journal of Finance, 32*(4), 1251–1266.
Smith, V. L. (1976). Experimental economics: Induced value theory. *The American Economic Review, 66*(2), 274–279.
Stigler, G. J. (1976). The xistence of x-efficiency. *The American Economic Review, 66*(1), 213–216.
Von Pischke, J. D. (1996). Measuring the trade-off between outreach and sustainability of microenterprise lenders. *Journal of International Development, 8*(2), 225–239.

APPENDIX A

Tables 9 and 10

Table 9. *Output distance frontier results*

Variable	Parameter	Std.Error
Deterministic component of stochastic Frontier model		
Constant	2.74985***	(0.04141)
ln(number of loans)	–1.06145***	(0.01530)
ln(yield)	0.05030***	(0.00741)
ln(financial expenses)	–0.03084***	(0.00390)
ln(administrative expenses)	0.01899	(0.02320)
ln(personnel expenses)	–0.21316***	(0.02663)
$1/2\ln(\text{number of loans})^2$	0.04636***	(0.00418)
$1/2\ln(\text{yield})^2$	–0.02512***	(0.00169)
$1/2\ln(\text{financial expenses})^2$	0.05591***	(0.00136)
$1/2\ln(\text{administrative expenses})^2$	0.00049	(0.00595)

(*continued on next page*)

Table 9—(*continued*)

Variable	Parameter	Std.Error
1/2ln(personnel expenses)^2	0.09501***	(0.00647)
ln(number of loans) × ln(yield)	0.00171***	(0.00008)
ln(number of loans) × ln(financial expenses)	0.00047***	(0.00009)
ln(number of loans) × ln(administrative expenses)	0.00077***	(0.00026)
ln(number of loans) × ln(personnel expenses)	−0.00076**	(0.00031)
ln(yield) × ln(financial expenses)	−0.00031***	(0.00006)
ln(yield) × ln(administrative expenses)	0.00026*	(0.00016)
ln(yield) × ln(personnel expenses)	0.00017	(0.00016)
ln(financial expenses) × ln(administrative expenses)	−0.00006	(0.00016)
ln(financial expenses) × ln(personnel expenses)	−0.00031**	(0.00016)
ln(administrative expenses) × ln(personnel expenses)	−0.00070**	(0.00036)
ln(number of loans) × D_{Bank}	−0.00379	(0.00324)
ln(number of loans) × $D_{\text{Cooperative or credit union}}$	0.00177	(0.00303)
ln(number of loans) × $D_{\text{Non-bank financial institution}}$	0.01007***	(0.00268)
ln(number of loans) × $D_{\text{Rural bank}}$	0.00606	(0.01090)
ln(yield) × D_{Bank}	0.00334*	(0.00203)
ln(yield) × $D_{\text{Cooperative or credit union}}$	0.00417**	(0.00176)
ln(yield) × $D_{\text{Non-bank financial institution}}$	0.00095	(0.00178)
ln(yield) × $D_{\text{Rural bank}}$	−0.00535	(0.00543)
ln(financial expenses) × D_{Bank}	0.00050	(0.00234)
ln(financial expenses) × $D_{\text{Cooperative or credit union}}$	−0.02387***	(0.00186)
ln(financial expenses) × $D_{\text{Non-bank financial institution}}$	−0.00856***	(0.00131)
ln(financial expenses) × $D_{\text{Rural bank}}$	0.00191	(0.00345)
ln(administrative expenses) × D_{Bank}	0.01313*	(0.00673)
ln(administrative expenses) × $D_{\text{Cooperative or credit union}}$	0.01074***	(0.00384)
ln(administrative expenses) × $D_{\text{Non-bank financial institution}}$	0.01139**	(0.00528)
ln(administrative expenses) × $D_{\text{Rural bank}}$	0.01157	(0.01575)
ln(personnel expenses) × D_{Bank}	−0.02577***	(0.00611)
ln(personnel expenses) × $D_{\text{Cooperative or credit union}}$	−0.00633	(0.00412)
ln(personnel expenses) × $D_{\text{Non-bank financial institution}}$	−0.01433***	(0.00520)
ln(personnel expenses) × $D_{\text{Rural bank}}$	−0.01687	(0.01906)
Variance parameters for compound error		
λ	2.30993***	(0.21163)
σ_u	0.28232***	(0.01666)

Notes: $^{*}/^{**}/^{***}$ signifies statistical significance at the 10/5/1% level. Log likelihood function value is 1,683.359; Kodde and Palm (1986) test for wrongly skewed residuals, at 95% = 10.371, at 99% = 14.325. To correct for spurious interaction terms, all variables in the translog have been transformed following the Frisch-Waugh theorem. To control for possible multicollinearity, the variables that explain μ have been orthogonalized. $\lambda = \sigma_u/\sigma_v$, i.e., the ratio of inefficiency and noise. σ_u is the standard deviation of (untransformed) inefficiency.

Table 10. *Group composition criteria*

Characteristic	Group	Sorting criteria
Breadth of outreach	Small breadth	Number of borrowers < 10,000
	Medium breadth	Number of borrowers 10,000–30,000
	Large breadth	Number of borrowers >30,000
Depth of outreach	Low end	Depth < 20% OR average loan size < USD 150
	Broad	Depth between 20% and 149%
	High end	Depth between 149% and 250%
	Small business	Depth over 250%

Notes: depth = Avg. Loan balance per borrower/GNI per capita. Criteria defined at http://www.mixmarket.org/about/faqs#calculations1.