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Mission Drift or Specialization: Determinants of Financial and Social Efficiency of Microfinance Institutions in Ecuador*

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Abstract

In this paper, we analyse the factors that influence both financial and social performance of MFIs in Ecuador, in order to detect mission drift. The methodology applied is a two-stage Data Envelopment Analysis (DEA) using a balanced panel of 35 MFIs belonging to the Red Financiera Rural (RFR), a national network, for the period 2010-2016. Our results are consistent with the hypothesis of mission drift and point to the key role of the lending methodology in driving the efficiency score results. Individual lending shows a significant positive effect on financial efficiency scores and a significant negative effect on social efficiency scores.

JEL Codes: O16, G21, C44
Keywords: Mission drift, microfinance institutions, DEA, Ecuador

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1 Introduction

The current face of the micro-finance industry has its origins in the nineteen-seventies, with parallel experiments in Asia and in some countries of Latin America. In 1974, Muhammed Yunus' Grameen Bank began providing small credits to poor women in Bangladesh, based on the concept that the "lack of access to credit was one of the fundamental barriers to overcome poverty". At roughly the same time (1972), in Recife (Brazil), *Projeto Uno* was the first program of micro-finance in Latin America, followed by other programs in the Dominican Republic (*Banco Ademi*) and El Salvador (*Fede-crédito*). The "revolution" of microcredit then spread all over the world, questioning preconceived notions of what poor households could do and showing the potential of innovative contracts and institutions to bring about financial inclusion (Berger et al., 2006; Armendáriz and Morduch, 2010).

Microfinance institutions (MFIs) are sometimes called "double bottom-line" institutions, thus emphasising their potential to achieve financial sustainability and poverty outreach at the same time. But there is an ongoing debate about whether MFIs can really meet both objectives, or if these are mutually exclusive instead. Some authors suggest that there is a trade-off between sustainability and outreach that can drive institutions to increase the size of their loans in order to widen their financial margins, leading them to move upmarket in the long run, serving less poor clients that do not belong to the traditional micro-finance targets of women, people living in rural areas and other groups traditionally excluded from financial services (Yaron, 1994; Hulme and Mosley, 1996; Mersland and Strøm, 2010; Hermes and Lensink, 2011). This process is sometimes called *mission drift*.[1]

Assessing the presence of mission drift is a difficult task, since there are other potential motives for increases in average loan size that do not necessarily affect outreach negatively, e.g. "progressive lending", which occurs when old clients that have shown good repayment records have access to higher credit ceilings in the subsequent credit cycles; or "cross-subsidisation", i.e. catering to unbanked wealthier clients in order to be able to reach more poor clients with smaller loan sizes, which are more expensive.[2]

In this paper, we analyse which are the factors and determinants that influence both financial and social performance of MFIs in Ecuador using as a unit of analysis member institutions of *Red Financiera Rural* (RFR),[3] a national network, to explore the possibility of detecting mission drift. The methodology applied is a two-stage Data Envelopment Analysis (DEA) to measure efficiency in terms of sustainability and outreach using a balanced panel of 35 MFIs for the period 2010-2016.

The main contribution of this paper is to use the efficiency scores for MFIs estimated using a two-stage DEA procedure to investigate the link between mission drift and the use of individual lending methodologies. This paper is organised as follows: Section 2 presents the specific context in which we analyse the efficiency of MFI institutions in Ecuador. Section 3 briefly reviews the literature and describes the studies related with our approach that have been conducted so far using non-parametric methods. Section 4 describes the methodology and data. The results obtained are described in Section 5, and Section 6 summarises the main conclusions as well as the possible applications for further research.

[1]Note that we use the term "mission drift" in a somewhat different sense than Copestake (2007), who defined it as a process of "*ex-post changes in stated preferences to fit unplanned performance outcomes*". His definition requires information not just about the performance of institutions, but also about their targets and goals.

[2]For a further discussion see Armendáriz and Szafarz (2011).

[3]In 2016 the institution changed its name to *Red de Instituciones Financieras de Desarrollo* (RFD).

2 The Microfinance Sector in Ecuador

Microfinance markets in Latin America show differences with other markets such as those of Asia and Sub-Saharan Africa. In Latin America MFIs are more commercially-oriented, with higher levels of financial sustainability and less dependence on donations (Armendáriz and Szafarz, 2011). There are also differences regarding outreach: Latin American MFIs target better-off clients and build larger average loan portfolios than those in Asia.[4] MFIs in Ecuador share these general characteristics with the Latin American market.

The financial system in Ecuador has been traditionally divided into regulated and unregulated institutions. The "regulated" sector covered all the institutions, both private and public, that were under the Banking Supervisory Agency's *Superintendencia de Bancos y Seguros* (SBS). This included, on the private side, banks, finance companies, mutual organisations, non-bank financial institutions (NBFIs), and Credit Unions and Cooperatives (CUCs) that were "large enough" to be supervised (assets greater than USD $10 million). In contrast, the "non-regulated" sector included those small CUCs created under the *Ley de Cooperativas* that did not met the size requirements of the SBS, non-governmental organisations (NGOs), and member-based organisations that where part of the informal sector, such as savings banks (*cajas solidarias*), rotating savings and credit association (ROSCAS), village banks (*Bancas Comunales*) and other credit and savings associations.

In recent years, reforms and regulatory measures have transformed the financial system in Ecuador. The Constitution approved in 2008 defined the financial system as composed of three sectors: public, private and "popular and solidarian" (P & S). The new P& S sector was legally described in the *Ley de Economía Popular y Solidaria* passed by Congress in 2011, as the sum of three sub-sectors: CUCs, support organisations and member-based structures, thus eliminating the dual legal framework for CUCs.[5] They were put under the supervision of a new agency called the *Superintendencia de Economía Popular y Solidaria* (SEPS).

Red Financiera Rural (RFR) legally started in 2000 as a national network of different institutions gathered in the *Grupo Sistema Financiero Alternativo* that were concerned about three major aspects: law and regulation of micro-finance institutions, specialised microcredit methodologies and training; and access to financial services for medium, small and micro enterprises, especially in rural and peri-urban areas (RFR, 2003).[6] It includes different organisations specialised in micro-finance such as Banks, CUCs, financial and non-financial NGOs, second-tier financial institutions, and local networks.[7] Although not all MFIs in the country are members of RFR, the network includes many of the larger ones, representing around 58% of the total microcredit borrowers and 55% of the gross loan microcredit portfolio in the whole of Ecuador(EQUIFAX, 2015).

The mission statements of RFR have changed from poverty reduction objectives to social and financial inclusion for vulnerable populations. In 2003, its mission was to

[4]Their clientele lives in urban areas in a higher proportion, and is much more balanced in terms of gender (60% of women, against 80% in Asia). Besides, the percentage of individual lending contracts is around nine times that of South Asian MFIs. See CAF (2011).

[5]As well as recognising member-based organisations for the first time.

[6]In addition to be recommended by two current members, prospective members of RFR must meet the following criteria: to have at least 45% of their portfolio in microcredit, to apply a specialized microcredit methodology based on average outstanding loan portfolio, to have an adequate profile of clients, and to show enough outreach (RFR, 2014).

[7]By law, only banks, CUCs and NGOs are allowed to provide loans (or any other services) directly to the public.

"*promote the creation of tools, mechanisms and processes to overcome poverty as well as social and gender inequality through sustained growth and enhanced productivity of small and medium producers in rural and peri-urban areas*" emphasising the importance of strengthening MFI members (RFR, 2003). In recent years, their focus is on becoming a "*benchmark organization*" that represents common interests of the different stakeholders to develop micro-finance, to influence public policies, to strengthen MFI members and to promote social and financial transparency in order "*to contribute improving living conditions of vulnerable people in Ecuador*" (RFR, 2013).[8] These changes in RFR's goal preferences could be explained by the fact that most of its members have financial inclusion as its main goal. Gender-oriented targets are prominent especially for NGOs although targeting women remains relatively low compared to other targets.

3 DEA Estimation of MFIs' Performance

The literature examining MFIs' performance through efficiency analysis, though not very large, has increased rapidly in recent years. The standard evaluation of the performance of MFIs follows the dual approach advanced by Yaron (1994) which takes "financial sustainability" and "outreach" as the aims guiding the institutions' activities. Success in attaining such objectives is traditionally monitored by compiling a set of ratio indicators that can be related to them.[9] Recently, however, frontier techniques for efficiency measurement, premised on the idea of estimating distances between observed performance points and a frontier of best practices, are increasingly employed as more sophisticated benchmarks for MFI performance.

Frontier techniques allow the researcher a fairly wide range of options. In order to get estimates of the efficiency scores for the individual decision-making units (DMUs) under analysis several methodological decisions need to be taken. When the DMUs are financial institutions, the first decision is about how to conceptualise their operation. The "intermediation" view sees financial institutions as mainly collecting deposits and making loans, with the aim to generate profits (Athanassopoulos, 1997). In contrast, the "production" view portrays financial institutions as users of physical resources (inputs) such as labor and capital, with the aim to produce services (outputs) such as savings and credits (Berger and Humphrey, 1997). Regarding MFIs, the production view is considered as the most suitable.[10] In our case, this is reinforced because current regulations in Ecuador do not allow non-governmental organisation (NGOs) to collect deposits from the public.

Production frontiers can be estimated by parametric methods (the so-called Stochastic Frontier Analysis or SFA) or by non-parametric ones. The non-parametric approach, and in particular the technique known as Data Envelopment Analysis (DEA), is usually preferred for measuring performance in MFIs due to its flexibility regarding data requirements and sample size.[11]

There is a growing literature of DEA efficiency estimations for MFIs.[12] However,

[8]The definition of vulnerable population depends on each MFI and can include low income, poor and very poor population, as well as people with lower education levels, women, micro and small business and other groups without access to financial and non-financial services (RFR, 2014).

[9]See Farrington (2000) for a fairly complete list of indicators and Cull et al. (2007) for a large comparative study finding evidence of mission drift linked to the use of individual lending methodologies.

[10]See, e.g., the argumentation in Gutiérrez-Nieto et al. (2009).

[11]Some studies, like Nghiem et al. (2006) or Annim (2012) have compared SFA and DEA measurements of MFI efficiency, finding no great differences among them.

[12]See, e.g., Gutierrez-Nieto et al. (2007), Bassem (2008), Gutiérrez-Nieto et al. (2009), Haq et al. (2010), Kablan (2012), Segun and Anjugam (2013), Piot-Lepetit and Nzongang (2014).

basic DEA estimations suffer from the inability to make statistical inference and by biasedness in case of measurement errors and/or noisy data (including outliers and small sample sizes). In order to deal with such issues, we adopted Simar and Wilson (2007) proposal of using double boot-straping and truncated regression on a two-stage DEA, as some very recent contributions, like Abdelkader et al. (2014), Wijesiri et al. (2015a), Wijesiri et al. (2015b), Cornée and Thenet (2016) or Bibi et al. (2017) have also done.

Results vary according to the data and methodological specifications used. Some studies, e.g. Gutiérrez-Nieto et al. (2009) and Annim (2012), use the information provided by the Microfinance Information Exchange (MIX) market, which provides a comprehensive and up-to-date global database on MFIs, in order to estimate global frontiers for micro-finance activity. These studies try to identify if there is evidence of a trade-off between financial and social efficiency or if they are complementary aspects of general efficiency instead, but the results they get are diverse and sometimes contradictory.

These discrepancies in results are not surprising if we take into account the heterogeneity of the institutions included in the estimations. The orientation and functional roles of MFIs vary widely, suggesting that different institutions will work with diverse production functions. This question is addressed in some cases, e.g. Wijesiri et al. (2015b), by using meta-frontier techniques to estimate different production frontiers for different groups of observations. Usually, the results show that the geographic location of the MFIs, in a wide, (sub-)continental sense, does significantly modify the efficiency measurements. Other studies take a more local approach, using information about MFIs in a particular area of the world (e.g. Bibi et al. (2017) for South Asia, Cornée and Thenet (2016) for Peru and Bolivia) or within the borders of one country (e.g. Piot-Lepetit and Nzongang (2014) for Cameroon, Wijesiri et al. (2015a) for Sri Lanka), and they also show wide divergences in results among countries.

Another important source of heterogeneity for MFIs is their different legal status. Most of the studies referenced above take into account the legal status of each individual MFI, sometimes estimating separate frontiers for each type of institution, other times including the type of institution as a explanatory variable at the second stage of a 2-stage DEA. While the results are, once more, highly idiosyncratic, there are a good number of estimations (Haq et al. (2010), Annim (2012), Wijesiri et al. (2015a), Cornée and Thenet (2016) among others) that estimate relatively higher scores (both for financial as well as for social efficiency measures) for NGOs than for other institutions.

4 Methodology and Data

In order to estimate a production frontier, it is necessary to assume the nature of the returns to scale involved in production. When variable returns to scale (VRS) are assumed it is then necessary to take into account the orientation of the frontier estimation. In the input-oriented (output-oriented) estimation the aim is to reduce (increase) the amount of inputs (outputs) as much as possible until the frontier is reached while keeping the outputs (inputs) unchanged. The decision between one or the other orientation must be made according to whether it is considered that the decision-maker has control over the inputs or over the outputs (Daraio and Simar, 2007). In the case of MFIs, the usual assumption is that their managers have more control over the inputs, and therefore we assume an input-oriented framework.

As stated in the previous section, we used a two-stage double bootstrap DEA with truncated regression. In the first stage, we computed efficiency scores using a standard

DEA procedure, solving the following linear program:

$$\theta_k^* = \min\{\theta > 0 | y_k \leq \sum_{i=1}^{n} \gamma_i y_i^*; \theta x_k \geq \sum_{i=1}^{n} \gamma_i x_i^*; \sum_{i=1}^{n} \gamma_i = 1; \forall i = 1, \ldots, n\}$$

where θ_k^* is the input-oriented technical efficiency score of the k DMU (MFI institution), x the vector of inputs, y the vector of outputs, γ a vector of shadow prices, n the number of DMUs, and $*$ denotes values corresponding to the optimal solution.

Simar and Wilson (1998) showed that non-parametric efficiency scores are biased by construction. We followed their adoption of a bootstrap algorithm to estimate bias-corrected scores and to construct their confidence intervals. In order to avoid the risk of inconsistency in estimating technical efficiency considering constant returns to scale (CRS) when this assumption does not hold, or a loss of statistical efficiency if we wrongly assume VRS, we have tested the hypothesis regarding returns to scale as suggested by Simar and Wilson (2002). They proposed a bootstrap procedure to test the more restrictive model of CRS against the VRS. If there is no evidence to the contrary, there is no point in estimating scale efficiency.

Regarding the second stage, Simar and Wilson (2007) criticised the usual approach of using censored (tobit) regression to investigate the determinants of the efficiency scores, showing that, as input and output variables are correlated with explanatory variables, these are also correlated with the error term. We followed their procedure of employing a bootstrap truncated regression procedure, where the bias-corrected scores obtained in the first stage ($\hat{\theta}_i^*$) are regressed on a set of explanatory variables (z_i):

$$\hat{\theta}_i^* = \alpha + \beta z_i + \epsilon_i \tag{1}$$

where α is a constant term, β is a vector of parameters, and ϵ_i is a random uncorrelated term.

Our database includes the 35 institutions from *Red Financiera Rural* (RFR) that reported financial information for each and all of the years in the period 2010-2016 (RFR, 2017). These include five banks, eighteen CUCs and eleven NGOs.

We performed a two-stage DEA following a production approach. A relevant decision within this framework is the selection of input and output variables to be included in the estimation of the production frontier. In the case of MFIs, the input measures more frequently used in the literature are total assets, operating expenses, and the number of employees.[13] On the other hand, the selection of output variables is widely used in the literature to differentiate between financial and social efficiency measurement.[14] Financial outputs are usually measured by financial revenues and the size of the gross loan portfolio, while measures of social outputs are commonly related to the concept of outreach and usually include the number of women borrowers ("depth of outreach") and the number of total borrowers ("breadth of outreach").[15]

[13] Other measures of capital like financial expenses, total expenses, equity or cost-per-borrowers and cost-per-savers ratios are less common, as is the case for measures of labor like labor personnel expenses and the number of loan credit officers.

[14] See e.g., Gutiérrez-Nieto et al. (2009), Annim (2012), Piot-Lepetit and Nzongang (2014), Wijesiri et al. (2015a), Wijesiri et al. (2015b), Cornée and Thenet (2016), Bibi et al. (2017).

[15] There are other, more sophisticated, social output variables like, e.g., the indicator of benefit to the poorest used by Gutiérrez-Nieto et al. (2009). This indicator includes the average loan portfolio relative to Gross National Income, therefore being more accurate in cross-country analysis, but only a few institutions can provide the level of detailed information required to compute it.

Table 1: Definitions of inputs and outputs for DEA models.

Symbol	Name	Definition	Unit
Input T	Total expenses	Financial Expenses + Impairment Losses + Operating Expenses	$
Input E	Personnel	Total number of staff members	Number
Output L	Gross loan portfolio	Outstanding principal balance of all outstanding client loans (including current, delinquent, and renegotiated)	$
Output R	Financial Revenue	Interest, fees & commissions incurred on the loan portfolio & other financial assets + other operating revenue	$
Output M	Number of microcredit borrowers	Number of active microcredit borrowers	Number
Output W	Number of active women borrowers	Number of active borrowers who are women	Number
Output B	Number of active borrowers	Number of active borrowers	Number

Note. Authors' elaboration based on RFR (2010-2017).

The input variables we selected are total expenses (T)[16] and the number of total employees (I).[17] As financial outputs, we include the gross loan portfolio (L) and financial revenue (R), whereas as social efficiency outputs we define *breadth of outreach* as the number of all borrowers (B) and *depth of outreach* as the number of women (W) and microcredit borrowers (M).[18] The definitions of the different inputs and outputs can be found in Table 1.

Figure 1 illustrates descriptive statistics of input and output variables by type of

[16]We explored using financial expenses, and also operating expenses plus impairment losses instead of total expenses, as in Annim (2012). Estimations using operating expenses yielded similar results to the ones here presented, with the differences focused on the models including financial revenue as an output variable. See Appendix A.

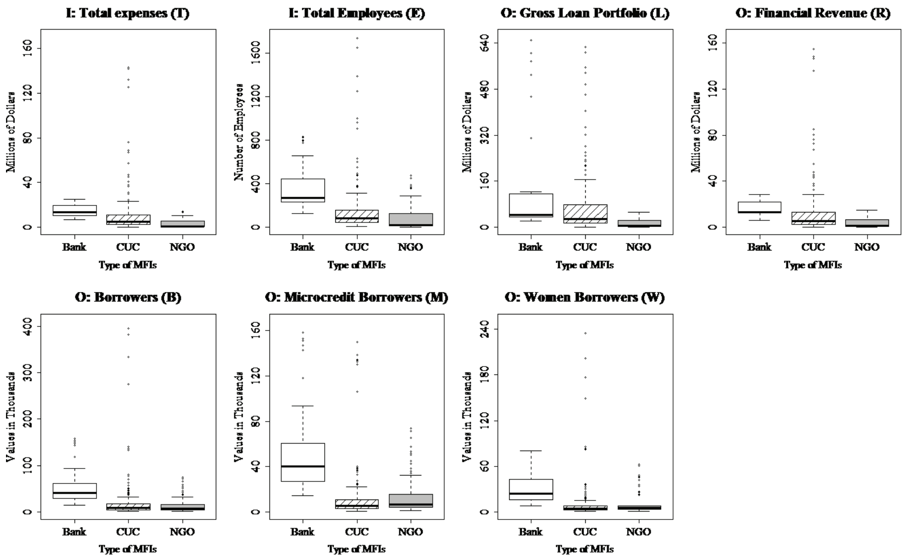
[17]We did not use any measure of physical inputs, like e.g. office space, because they are all strongly correlated with size.

[18]Depth of outreach is usually measured by the average loan portfolio; see e.g. Hulme and Mosley (1996), Schreiner (2002), Cull et al. (2007), Armendáriz and Morduch (2010). However, standard DEA models do not consider ratios as output, since the denominator can become an input in the estimation process and may result in incorrect efficiency scores; see Emrouznejad et al. (2010). We chose microcredit borrowers to measure depth of outreach because they are the main target clients of RFR (RFR, 2014), and they face the lack of access to financial services as one of the main barriers in order to improve their business (SALTO-USAID, 2015). We included also the number of women, because it is one of the main objectives of microfinance; see Morduch (1999), Dowla and Barua (2006) or Armendáriz and Morduch (2010). Due to the lack of information we included only outreach outputs as measures of social performance, excluding other important targets for MFIs such as geographical outreach (rural clients), or adapted services and social responsibility, as in e.g. Bédécarrats et al. (2015).

institution. It can be easily observed that banks are large MFIs, both in gross loan portfolio and in number of borrowers, and that NGOs are smaller. In contrast, CUCs show wide ranges in all input and output measures, including both relatively small institution and very large ones.

In the first-stage, after testing for returns to scale we calculated efficiency scores using an input-oriented approach (minimising inputs to a given output and technology) with mean normalised data. We have created six different model specifications: TE-L, TE-R, TE-LR as measures of technical financial efficiency and TE-M, TE-W and TE-B as measures of social efficiency.

Figure 1: Boxplots of inputs and outputs for DEA estimations.



Note. Authors' elaboration based on RFR (2010-2017)

We obtained bias-corrected technical efficiency scores using the bootstrap method suggested by Simar and Wilson (2007). We are interested in exploring up to what extent our efficiency scores are correlated with traditional performance indicators (both related to financial and social targets).[19] Descriptive statistics for the indicators considered are shown in Table 2.

[19]The indicators are divided into five groups: i) Overall Financial Performance, ii) Outreach, iii) Risk, iv) Financing Structure and v) Efficiency and Productivity. Their definitions and detailed information by type of institution can be found in Appendix B.

Table 2: Descriptive statistics for performance ratios.

	Mean	**SD**
Overall Financial Performance		
ROE	0.127	0.16
ROA	0.021	0.02
OSS	1.191	0.34
Outreach		
Women borrowers (pct.)	0.539	0.13
Risk		
Portfolio at risk > 30 days	0.054	0.03
Financing Structure		
Cost-of-funds ratio	0.059	0.02
Yield on gross loan portfolio	0.200	0.05
Efficiency and productivity		
GLP/staff members	348 985	197 308
Borrowers/staff members	148.718	81.80
Personnel allocation ratio	0.338	0.15
Personnel allocation ratio (women)	0.153	0.10
Operational Efficiency Ratio	0.116	0.06

Note. Authors' elaboration based on RFR (2010-2017).

In the second-stage we then run a truncated regression on a set of external explanatory variables of MFIs' efficiency, which are summarized in Table 3, and include institutional characteristics such as institutional type and credit methodology[20] and a dummy variable for each year of the period 2010-2016.

MFIs report their loan portfolio by the credit methodology applied using three categories:[21] individual lending (single-client lending where repayment relies solely on the individual), group lending (a group of individuals provide collateral or loan guarantee through a group repayment pledge), and village banking (clients form groups of approximately 10-30 individuals that are autonomously responsible for leadership, bylaws, bookkeeping, fund management and loan supervision).

[20] It is important to notice that despite the new regulatory framework, CUCs began to report information to the SEPS only after December 2012. Therefore, regulation (whether the MFIs were under the supervision of SBS) can be considered in the case of CUCs as a proxy of size. We decided, then, to exclude it from our set of explanatory variables.

[21] See MIX (2004).

Table 3: Definitions of explanatory variables for 2nd stage.

Name	**Definition**
MFI Type	1 = Bank 2 = Credit Union/Co-operative (CUC) 3 = Non-governmental organization (NGO)
Credit methodology	0=Group lending + Village banking 1= Individual lending
Year	Takes values from 1 to 7 for each year of the period 2010-2016

Note. Authors' elaboration based on RFR (2010-2017).

The use of the different credit methodologies is described in Table 4. MFIs in RFR grant loans using mostly and increasingly individual lending methods. Only NGOs rely substantially (almost 50% on average) on group lending techniques for their credit operations.

Table 4: Group-based lending methodology: MFI members of RFR.

	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Bank	0.456	0.226	0.185	0.145	0.200	0.286	0.274
CUC	0.113	0.095	0.108	0.103	0.085	0.076	0.078
NGO	0.504	0.552	0.562	0.550	0.556	0.485	0.490

Note. Authors' elaboration based on RFR (2010-2017).

5 Results

The choice of assumptions regarding returns to scale in the estimation of technical efficiency may lead to inconsistent estimators if constant returns to scale (CRS) are wrongly assumed, or to a loss of statistical efficiency when the wrong assumption imposed is that of variable returns to scale (VRS). In order to avoid these potential problems, we have tested the CRS hypothesis following the bootstrap procedure suggested by Simar and Wilson (2002).[22] Thus, we built a test statistic by computing the mean of ratios of the VRS and CRS efficiency scores with our data, and then obtain p-values using the bootstrap algorithm described above. We find that we cannot reject the null hypothesis of CRS when we use gross loan portfolio (L) and all outreach outputs (M, W, B), but we can reject it (and, hence, assume VRS) when we include financial revenues as output.[23]

[22]This procedure uses the consistency properties of the estimators to build the test flor the CRS hypothesis. VRS estimators are always consistent, while CRS estimators are only consistent if the CRS hypothesis is true. Thus, if the CRS hypothesis were true, the two sets of estimators would be very similar.

[23]All the reported results were obtained using the FEAR package in R. In this particular case, we run 2,000 replicas.

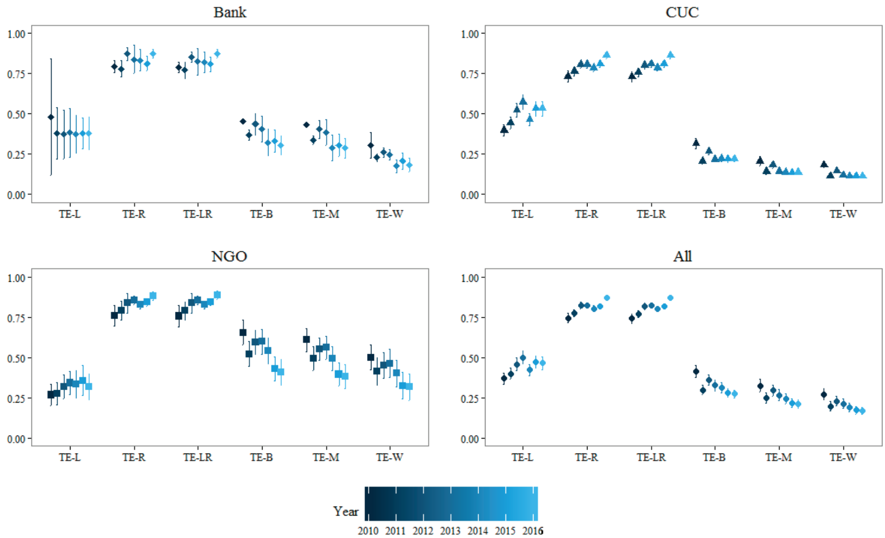
Table 5: Testing Returns to Scale (p-values).

	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
TE-L	0.970	0.908	0.933	0.869	0.668	0.654	0.602
TE-R	0.003	0.000	0.001	0.000	0.001	0.007	0.000
TE-LR	0.011	0.001	0.005	0.000	0.000	0.009	0.000
TE-B	0.734	0.350	0.500	0.667	0.830	0.395	0.212
TE-M	0.813	0.519	0.710	0.864	0.894	0.569	0.461
TE-W	0.570	0.487	0.453	0.607	0.661	0.408	0.286

Note. Authors' elaboration based on RFR (2010-2017).

Figure 2 pictures the values of bias-corrected efficiency scores. The general trend was of increase in financial efficiency scores during the period combined with decline in the outreach efficiency scores. By type of institutions, CUCs show slightly higher financial efficiency scores when L is used as the output variable, while NGOs are consistently the more efficient institutions regarding our outreach measures. Banks show high variability in their financial efficiency scores, in particular when L is used as the output variable.

Figure 2: Patterns of MFI efficiency.

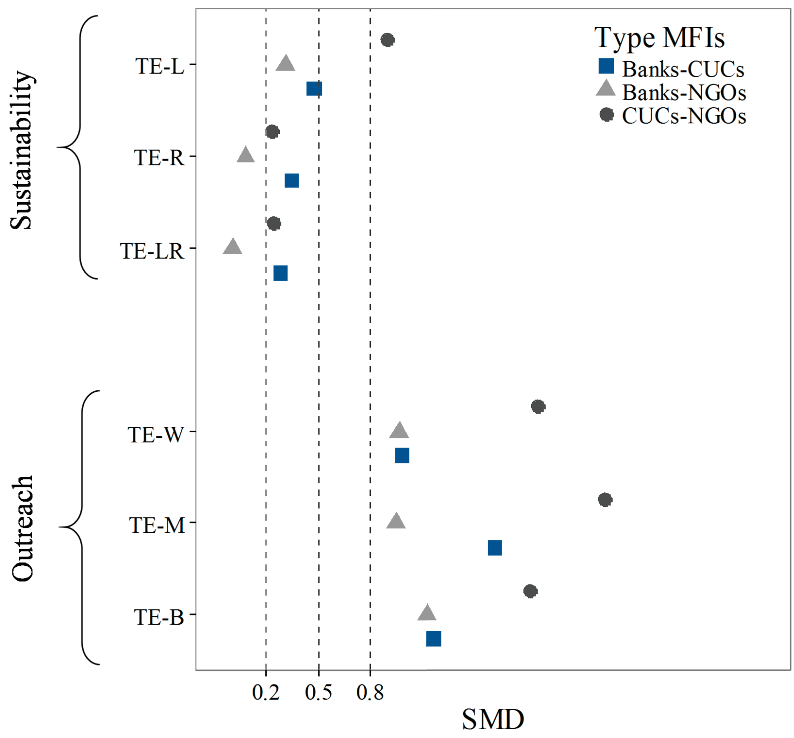


Note. The graph shows the mean values of the bias-corrected efficiency scores. Error bars represent 95% confidence intervals. CUC= Cooperative and Credit Unions. NGOs= non-governmental organization. Authors' elaboration based on RFR (2010-2017)

In Figure 3 we show the size of the differences between each type of MFI for both social and financial efficiency scores using pairwise comparisons of the standardised mean differences (SMD).[24] As seen in the figure, the differences in financial efficiency are, in general, small. This is not the case for social efficiency scores, where differences are large, in particular between CUCs and the other two types of MFIs.

[24]We use the cutoffs defined by Cohen (1992) (d=.20,.50,.80), corresponding to small, medium and large differences, respectively.

Figure 3: Standardized mean difference of social and financial efficiency scores by type of microfinance institutions.

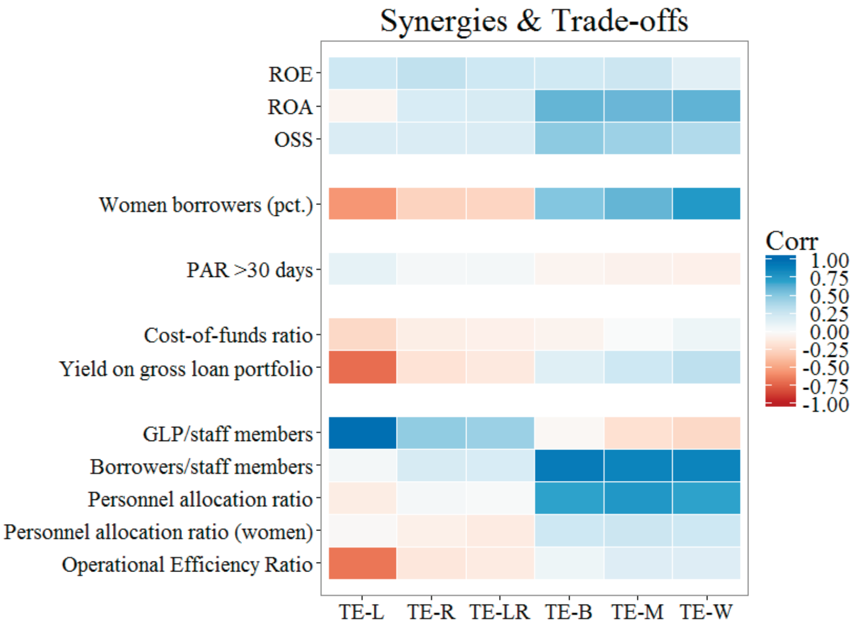


Note. The SMD was estimated using the *tableone* package in R (Yoshida and Bohn (2015)). Authors' elaboration based on RFR (2010-2017).

We explore the relationship of bias-corrected efficiency scores (financial and social) with a series of standard indicators of (financial and social) performance. The correlations for the pooled sample are shown in Figure 4. These results only describe associations between efficiency scores and traditional ratios. Although causal inferences cannot be made from them, we can nevertheless detect some possible complementarities and trade-offs by looking at the signs of the correlations.

In short, all indicators considered show strong positive correlation with some efficiency score, with the exceptions of ROE, the measure of portfolio-at-risk and the personnel allocation ratio for women, which show weaker correlations, and the cost-of-funds ratio, which is an inverse measure of productivity, and thus shows negative correlation with financial efficiency scores. More interestingly, some of the indicators that show positive correlation with social efficiency scores are, at the same time, negatively correlated with financial efficiency scores. This is the case for the percentage of female borrowers, as well as for the yield on the gross loan portfolio (GLP), that indicates the ability to generate cash financial revenues from interest, fees and commissions, regarding the efficiency in generating GLP as output. On the other side, apparent labor productivity measured as the size of GLP per staff member, an indicator positively associated with financial efficiency, shows negative correlation with social efficiency scores.

Figure 4: Correlation between efficiency scores and financial ratios (DEA-Bootstrap).



Note. Authors' elaboration based on RFR (2010-2017). N = 245.

In the second stage, we estimated a truncated regression on environmental external variables using maximum likelihood with 1,000 bootstrap replicas. The results are summarised in Table 6.[25] See Appendix C.

[25]Since DEA scores are biased by construction, we performed a principal component analysis for improving discrimination as suggested by Cinca and Molinero (2004) or Adler and Yazhemsky (2010), and then performed an OLS in a second stage. We implemented the methodology suggested by Banker and Natarajan (2008) to include DEA in the first stage followed by OLS in the second stage and estimated the relationship $\hat{\theta}_k^* = Z_i\beta + \epsilon_i$. The results were similar to the ones reported in Table 6 from the double bootstrap truncated regression. with equal signs but slightly different values for the coefficients, which may reflect the bias of DEA estimates identified by Simar and Wilson (2011).

Table 6: Determinants of bias-corrected efficiency scores (Truncated Regression, reference variables within parentheses).

	TE-L	**TE-R**	**TE-LR**	**TE-B**	**TE-M**	**TE-W**
MFI Type						
CUC	0.102	−0.081**	−0.064*	−0.136***	−0.230***	−0.114***
	(1.642)	(−2.711)	(−2.398)	(−4.353)	(−6.832)	(−4.105)
NGO	−0.006	0.064	0.075*	0.131***	0.102**	0.126***
	(−0.084)	(1.823)	(2.306)	(3.316)	(2.763)	(4.038)
Method						
I. Lending	0.298***	0.211***	0.199***	−0.120***	−0.184***	−0.250***
	(4.494)	(6.295)	(6.158)	(−3.379)	(−5.816)	(−7.332)
Year						
2011	0.036	0.029	0.027	−0.125**	−0.106*	−0.101**
	(0.648)	(0.785)	(0.746)	(−3.192)	(−2.455)	(−2.993)
2012	0.113	0.097*	0.091*	−0.052	−0.040	−0.053
	(1.933)	(2.519)	(2.476)	(−1.336)	(−0.970)	(−1.646)
2013	0.162**	0.095**	0.097**	−0.090*	−0.074	−0.073*
	(2.755)	(2.609)	(2.776)	(−2.344)	(−1.775)	(−2.230)
2014	0.069	0.063	0.066	−0.113**	−0.120**	−0.116***
	(1.160)	(1.749)	(1.914)	(−2.824)	(−2.700)	(−3.425)
2015	0.126*	0.082*	0.087*	−0.143***	−0.150***	−0.132***
	(2.105)	(2.220)	(2.457)	(−3.513)	(−3.354)	(−3.857)
2016	0.116	0.170***	0.172***	−0.154***	−0.158***	−0.143***
	(1.904)	(4.035)	(4.211)	(−3.664)	(−3.427)	(−3.797)
Constant	0.033	0.632***	0.621***	0.560***	0.576***	0.490***
	(0.394)	(14.044)	(14.184)	(11.559)	(11.711)	(12.093)
σ Constant	0.216***	0.124***	0.120***	0.140***	0.142***	0.122***
	(16.091)	(13.064)	(13.025)	(17.830)	(15.393)	(15.695)
Wald	73.807	61.399	60.541	195.846	304.194	177.394
ρ^2	0.495	0.506	0.510	0.725	0.798	0.808

Note. Z-values in parentheses are based on 1,000 bootstrap estimations of the truncated regression. Authors' elaboration based on RFR (2010-2017). N = 245. Sig.: *p< .05, ** p< .01, *** p < .001

The sharper ones are related to the lending methodology, suggesting the existence of a trade-off between financial and social efficiency for the institutions with higher percentages of their loan portfolio granted through individual lending methodologies.These

MFIs got lower scores in depth of outreach and higher scores in terms of profitability, in a way consistent with the results obtained by Cull et al. (2007). It is interesting to note that, in our sample, individual lending shows a high and significant negative correlation with the percentage of women borrowers, hinting at a negative relationship between MFI focused on female borrowers and efficiency in terms of sustainability, like the one found in Hermes et al. (2011).

A second outstanding result is the evidence about a gradually increasing negative effect for social (outreach) efficiency in the years 2014-2016 (taking 2010 as reference). One possible explanation for this can be ascribed to the medium-term impact of the approval of the *Ley de Economía Popular y Solidaria* that introduced entry barriers for CUC prohibiting its expansion and opening of new branches.

We have also included the type of institution in our regression as a potential determinant of the efficiency scores, taking Banks as the reference category. Banks are the MFIs with the highest profit levels and the ones with the larger number of borrowers. We found evidence of a statistically significant negative impact on social efficiency of an institution giving microcredit being a CUC, no matter how me measure the outreach outputs.

On the contrary, being an NGO rather than a Bank appears to have a positive effect on social efficiency. As this effect is present even if we consider all borrowers, this can be interpreted as lack of evidence that cross-subsidisation is taking place in the microcredit practices of the NGOs.

6 Conclusions

In this paper we estimated efficiency scores for 35 Ecuadorian MFIs from annual data corresponding to the period 2010-2016 using a two-stage double bootstrap DEA with truncated regression (Simar and Wilson, 2007). The MFIs included institutions of three different types: banks, CUCs and NGOs. We followed the production approach and estimated six different models using different definitions of the output variable. Three of the models tried to measure financial efficiency by defining an output variable related to the financial objectives of the DMUs, while the other three tried to measure social efficiency by defining an output variable related to the the social inclusion objectives of the DMUs.

After testing the hypotheses regarding returns to scale, we estimated two of the models (those containing financial revenues as an output variable) under the VRS hypothesis, and the other four under the CRS hypothesis. The values obtained for the efficiency scores were remarkably robust in five of the six different models, with the only exception of the model using GLP as an output variable (the TE-L model), and showed very few relevant differences among types of MFI. The higher variability of the scores obtained in this model and its lack of correspondence with the other two models and also among types of MFI led us to focus our interpretation of the results on the other five models.

The picture offered by the results of our estimations was of a group of MFIs highly and increasingly efficient on the financial side, but with low (except in the case of NGOs) and decreasing (without exception) social efficiency. These results can be considered as broadly consistent with the hypothesis that the MFIs analysed experience some form of "mission drift", and the consideration of the recent history of the regulation of MFIs in Ecuador combined with our results suggests that the main recent regulatory change, the approval of the *Ley de Economía Popular y Solidaria* did not help to correct this drift and maybe even could contribute slightly to it. Observing the correlations between our estimations of the efficiency scores and some of the more popular ratios used to describe financial and social efficiency of MFIs we found that, while most of them show the right type of correlation with the score reflecting the type of efficiency they intend to describe, very few show the stark trade-off between financial and social efficiency. In this respect, we found that the percentage of women borrowers is the ratio that best approaches this trade-off.

The results obtained by the truncated regression estimated in the second stage of our procedure reinforce the picture above described and point to the key role of the lending methodology used by the MFIs in driving the efficiency score results. Individual lending shows a significant positive effect on financial efficiency scores *and* a significant negative effect on social efficiency scores. Of the three types of MFIs analysed, only NGOs present a balanced mix between individual lending and group lending.

The main limitations of our analysis are those originated by the volume and quality of the information available. The number of institutions included in our analysis, while large enough relatively to the standards of the efficiency measurement literature, represent slightly less than half of the total microcredit loan portfolio of Ecuador. We could not even include all MFI members of RFR, because some institutions stopped reporting information or dropped out the network during our period of analysis. Besides, our choice of input and output variables as well as of control variables in the truncated regression were more limited than the ideal ones, because of the impossibility to get information about certain variables.

To sum up, our empirical results show that individual lending methodologies have a positive effect on financial efficiency, but negative on social efficiency. This suggests that trade-offs between social and financial outcomes are stronger than the synergies of providing financial services for vulnerable populations. Hence, the much-touted win-win relationship of micro-finance is not apparent in Ecuador, and it seems instead that targeting traditionally excluded groups, like women, comes with a price.

Our results suggest that exploring further the impact of lending methodologies on the trade-off between social and financial performance of MFIs is necessary in order to understand the nature of the mission drift many institutions seem to experience and to be able to design policies that can effectively prevent this drift without damaging the long-term sustainability of MFIs.

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Appendix A: Operating Expenses as Input Variable. Determinants of Bias-corrected Efficiency Scores

	OE-L	OE-R	OE-LR	OE-B	OE-M	OE-W
MFI Type						
CUC	0.089	0.158***	0.031	−0.109***	−0.204***	−0.097***
	(1.497)	(4.921)	(0.844)	(−3.644)	(−6.495)	(−3.399)
NGO	0.004	0.161***	0.062	0.179***	0.160***	0.178***
	(0.060)	(4.286)	(1.480)	(4.237)	(3.883)	(4.964)
Method						
I. lending	0.237***	0.136***	0.171***	−0.153***	−0.214***	−0.280***
	(4.211)	(3.553)	(4.574)	(−4.005)	(−6.114)	(−7.702)
Year						
2011	0.075	0.005	0.012	−0.123**	−0.112*	−0.134***
	(1.406)	(0.133)	(0.309)	(−2.949)	(−2.293)	(−3.764)
2012	0.132*	0.079	0.084*	−0.047	−0.028	−0.058
	(2.408)	(1.892)	(2.032)	(−1.213)	(−0.641)	(−1.721)
2013	0.182**	0.141***	0.152***	−0.075*	−0.068	−0.102**
	(3.258)	(3.301)	(3.583)	(−1.992)	(−1.625)	(−3.284)
2014	0.130*	0.234***	0.224***	−0.075*	−0.081	−0.109**
	(2.349)	(5.162)	(5.202)	(−1.971)	(−1.866)	(−3.277)
2015	0.167**	0.231***	0.232***	−0.088*	−0.097*	−0.108**
	(3.061)	(5.597)	(5.846)	(−2.249)	(−2.208)	(−3.144)
2016	0.145**	0.151***	0.153***	−0.105**	−0.109*	−0.101**
	(2.620)	(3.544)	(3.792)	(−2.699)	(−2.459)	(−2.987)
Constant	0.075	0.234***	0.317***	0.546***	0.561***	0.504***
	(0.992)	(5.404)	(6.723)	(10.602)	(10.526)	(11.833)
σ Constant	0.204***	0.164***	0.161***	0.141***	0.145***	0.124***
	(16.995)	(20.989)	(21.492)	(16.001)	(14.794)	(16.224)
Wald	79.122	121.182	122.438	225.388	329.676	272.211
ρ^2	0.222	0.304	0.285	0.564	0.671	0.706

Note. Z-values in parentheses are based on 1,000 bootstrap estimations of the truncated regression. Authors' elaboration based on RFR (2010-2017). N = 245. Sig.: *p< .05, ** p< .01, *** p < .001

Appendix B: Definitions of Financial Performance Ratios

Name	Definition
Overall Financial Performance	
ROE	(Net Operating Income - Taxes) / Average Total Equity
ROA	(Net Operating Income - Taxes) / Average Total Assets
OSS	Financial Revenue / (Financial Expense + Impairment Loss + Operating Expense)
Outreach	
Women borrowers (%)	Number of active women borrowers/ Number of active borrowers
Risk	
Portfolio at risk > 30 days	The value of all loans outstanding of microcredit that have one or more installments of principal past due more than 30 days (Includes unpaid principal balance and loans that have been restructured or rescheduled)
Financing Structure	
Cost-of-funds ratio	Weighted average rate paid on paying liabilities
Yield on GLP	Interest and Fees on Loan Portfolio/ Average Gross Loan Portfolio
Efficiency & productivity	
GLP/staff members	Gross Loan Portfolio/ Number of Personnel
Borrowers/staff members	Number of Active Borrowers / Number of Personnel
PAR	Number of Loan Officers / Number of Personnel
PAR (women)	Number of Loan Officers (women) / Number of Personnel
OER	Operating Expense / Average Gross Loan Portfolio

Note. Authors' elaboration based on RFR (2010-2017).

Appendix C: PCA/OLS Estimations.
Determinants of Bias-corrected Efficiency Scores

	TE-L	TE-R	TE-LR	TE-B	TE-M	TE-W
MFI Type						
CUC	0.000	−0.023	−0.030	−0.154***	−0.200***	−0.087**
	(−0.007)	(−0.729)	(−0.766)	(−4.337)	(−5.796)	(−3.231)
NGO	−0.032	0.121**	0.060	0.178***	0.144***	0.164***
	(−0.460)	(3.245)	(1.319)	(3.705)	(3.343)	(4.485)
Method						
I. lending	0.217***	0.266***	0.275***	−0.186***	−0.224***	−0.296***
	(4.545)	(6.918)	(7.329)	(−4.145)	(−5.806)	(−6.703)
Year						
2011	0.031	0.021	0.023	−0.108**	−0.076*	−0.065*
	(0.628)	(0.410)	(0.470)	(−2.744)	(−2.091)	(−2.115)
2012	0.060	0.098	0.092	−0.060	−0.042	−0.042
	(1.180)	(1.850)	(1.825)	(−1.546)	(−1.208)	(−1.464)
2013	0.079	0.102*	0.104*	−0.096*	−0.073*	−0.062*
	(1.609)	(1.968)	(2.103)	(−2.559)	(−2.144)	(−2.153)
2014	0.031	0.062	0.058	−0.102**	−0.084*	−0.074*
	(0.625)	(1.142)	(1.114)	(−2.578)	(−2.373)	(−2.477)
2015	0.061	0.079	0.081	−0.125**	−0.103**	−0.082**
	(1.211)	(1.508)	(1.600)	(−3.121)	(−2.930)	(−2.687)
2016	0.039	0.143**	0.121*	−0.135***	−0.111**	−0.089**
	(0.793)	(2.774)	(2.425)	(−3.344)	(−3.011)	(−2.895)
Constant	0.104	0.375***	0.304***	0.528***	0.581***	0.492***
	(1.463)	(6.588)	(5.234)	(9.526)	(11.274)	(10.711)
Wald	99.831	73.940	72.076	227.124	352.974	252.037
R^2	0.158	0.192	0.198	0.596	0.688	0.687

Note. Bias-corrected efficiency scores estimated using principal component analysis (Cinca and Molinero, 2004). Z-values in parentheses are based on 1,000 bootstrap estimations of the OLS regression. Authors' elaboration based on RFR (2017). Sig.: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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