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A data envelopment analysis of the global microfinance industry

Análisis envolvente de datos de la industria microfinanciera global

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Abstract

This work compares the technical efficiency of a global sample of private and publicly listed Microfinance Institutions (MFIs), and publicly listed commercial banks of a similar scale and geographical location. Two important research questions are addressed. The first one is: are public MFIs more efficient than non-public MFIs?; and, the second one is: how efficient are MFIs relative to "comparable" commercial banks? Our results indicate that publicly listed MFIs are more efficient than private MFIs when the latter operate at a suboptimal scale. That is, listed MFIs are able to grant the same amounts of loans, invest as much, and have the same range of profits but, at the same time, are more technologically efficient in reducing expenses and use less assets. Moreover, the results indicate that listed commercial banks are the least efficient of all types of financial services providers included in the studied sample.

JEL Code: C14, D02, G21
Keywords: Microfinance institutions; commercial banks; technical efficiency; data envelopment analysis; emerging countries

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Resumen

Este trabajo compara la eficiencia operativa de una muestra global de instituciones microfinancieras (IMF) privadas y que cotizan en mercados bursátiles, y la de bancos comerciales públicos. Se abordan dos preguntas de investigación: ¿son las IMF públicas más eficientes operativamente que las IMF no públicas?; y ¿qué tan eficientes son las IMF con respecto a bancos comerciales "comparables"? Nuestros resultados indican que las IMF que cotizan en Bolsa son más eficientes que las IMF privadas, cuando éstas operan con una escala subóptima. Es decir, las IMF públicas son capaces de conceder la misma cantidad de préstamos, invertir lo mismo, y obtener el mismo rango de beneficios, pero, al mismo tiempo, son tecnológicamente más eficientes en la reducción de los gastos, y utilizando menos activos. Además, los resultados indican que los bancos comerciales son los menos eficientes de todos los tipos de proveedores de servicios financieros incluidos en el análisis.

Código JEL: C14, D02, G21
Palabras clave: Microfinancieras; bancos comerciales; eficiencia técnica; análisis envolvente de datos; países emergentes

Introduction

One of the most relevant entrepreneurial initiatives to attack poverty in less developed regions of the world is related to the microfinance industry, which has blossomed at a slow but steady pace since the early 1970s. By 2011, MFIs already served around 150 million active customers worldwide (Chu, 2011), and the share of adults owning an account grew from 61% in 2014 to 69% in 2017 (Demirgüç-Kunt, Klapper, Singer, Ansar, & Hess, 2018). This constant growth seems stable, as MFIs' target market includes the portion of population with no access to banking services across the developing world.

But MFIs' economic importance goes beyond their aim to reduce income inequality by providing access to different financial products to the poor (Gutiérrez-Nieto et al., 2007; Hermes, 2014); they support microbusiness entities with financial services that facilitate their normal operation and allow their expansion to other market segments, other regions and other countries. In addition to the success record of MFIs in helping the poor start small-scale productive activities that improve their potential income, there also are multiplying effects in terms of employment creation, increased consumption, and associated investments (Fila, 2015). Considering that in many cases an important hurdle for the permanence, growth and consolidation of small and medium sized enterprises is the limited access they have to financial services, the MFI alternative opens new and brighter horizons (Ardic, Imboden, & Latortue, 2013).

Like other private business entities, MFIs obtain the resources they need to serve their customers from a variety of sources. Obtaining low cost funds is an important condition to pursue their poverty-reduction mission. So searching for grants and donations is very frequently the most important activity of some MFIs. At the other extreme of the continuum, some MFIs have developed a for-profit explicit interest, and market conditions may dictate them to charge high interest rates to their customers, potentially in conflict with the motivation to reduce poverty (Bos & Millone, 2015). Some reflection suggests that there is a "virtuous" middle point where MFIs can attain independence and long-term sustainability but, at the same time, make a significant contribution to improving the standard of life of large segments of the population by serving them with ad-hoc financial services.

The challenge faced by a large number of recently created MFIs is to transit from a status of Non-Governmental Organizations (NGOs) whose income is highly dependent on donations and forced savings, to licensed financial entities that generate an average business return on investment and become self-sustainable. Those MFIs face the opportunity to achieve a reasonable efficiency and scale of operation and, eventually, undertake the more ambitious challenge to issue stock in a public market. In effect, a moderately increasing number of MFIs are following that path and, by listing themselves in the stock market, they gain access to more stable funding through both debt and equity security issues. More stable sources of funds allow managers to focus their attention on their core business, improve efficiency and attract more clientele. However, once an MFI becomes publicly traded, it accepts new responsibilities and faces new challenges (Kar, 2013).

There is an ongoing debate on the subject, and that is one of the main motivations of the present study. According to Ardic, Imboden & Latortue (2013), governments of many emerging countries are nowadays increasingly making financial inclusion and the multiplication of efficient financial intermediary agents that serve the poor as two of their main public policy priorities. This necessity is sometimes exacerbated by turmoil episodes that produce serious global disarrangements, like the Great Depression of 2008-2009 proved (Wijesiri, 2016). MFIs need the resources to serve their markets and whether they achieve, or not, their objectives may depend on the type of funding they use. But the type of funding they use also has corporate governance implications that influence their operating and financial efficiency. In fact, Piot-Lepetit & Tchakoute Tchuigoua (2021) found that the MFIs' performance depends both on their ownership status and the financial environment in which they operate.

This work's first postulate is that the operating performance of different types of MFIs is not the same. It begins by comparing the relative efficiency of private and publicly listed MFIs and benchmarks them to listed commercial banks, all comparable in size and established in similar markets. As publicly traded entities enjoy easier access to funds through the financial markets and can focus more on their core business, it is hypothesized that publicly traded MFIs should be more efficient than private MFIs. A second postulate is that when compared to commercial banks, MFIs are at disadvantage due to the former's long-term developed abilities of being a financial services provider. Both publicly listed and

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non-listed Decision Making Units (DMUs)[2] of a similar scale and geographical location are compared in terms of their operating efficiency. A Data Envelopment Analysis (DEA) is performed with 81 DMUs to contrast these postulates empirically.

The DEA approach is a way to compute efficiency scores that allows for the disaggregation of efficiency in its two component parts: pure technical efficiency and scale efficiency. The former represents the success of an institution at converting inputs into outputs, and is related to managerial performance; the latter measures whether the institution operates with an optimal scale (Eken & Kale, 2014). When both measures merge into a single technical efficiency score, the overall success of an entity's ability to convert inputs into outputs at the right scale of operations is obtained.

The evidence confirms that public MFIs enjoy a comparative advantage with respect to non-public MFIs in terms of technical efficiency which, from a business perspective may be interpreted as a consequence of the fact that while non-public MFIs spend a significant part of their time scouting for funds from different institutional and individual donors. For that reason, non-public MFIs do not focus on strategy design and execution, while publicly traded MFIs have access to capital markets and can issue both bonds and stock to fund their operations in a more expedite way. However, the analysis of the results challenges the a priori assumption that commercial banks are more efficient than MFIs.

The following section of this paper presents a comprehensive literature review on productivity and efficiency studies, different methods to measure efficiency, and the efficiency of banks and MFIs. The third section presents the research design and methodology, where the two research questions are explained, as well as the analyzed database and variables. The fourth section contains the results of which type of financial firms had the highest efficiency scores, and their interpretation. During the sample period, the DEA analysis output shows that listed MFIs are more frequently "purely technical efficient" than the other two types of firms; and that private MFIs are the most technically efficient in many more quarters than their public counterparts. A striking finding is that listed commercial banks appear to be the least efficient of all types of financial services providers in the analysis. Finally, the fifth section presents some interesting conclusions about the microfinance industry and the importance it should be taken by policy makers in pursue of developing financial inclusion in their countries.

[2] Decision Making Units (DMUs) are any set of peer units or organizations (e.g., hospitals, schools, factories, banks, etc.)

Literature review

Productivity and efficiency

Efficiency assessment is based on the theory of production functions, i.e., the maximum level of production that can be achieved given a specific combination of production factors (Pindyck & Rubinfeld, 2001). Hence, producers' main goal is to maximize production, given the available technology. This goal is known as a productive efficiency. However, producers do not always achieve their goal as there are exogenous factors that may deviate their activity from the optimal production frontier (Kumbhakar & Lovell, 2000). Only those producers that manage to be on the optimal production frontier are technically efficient. A firm that is technically efficient might still be able to improve its productivity by exploiting scale economies (Coelli, Rao, O'Donnell, & Battese, 2005).

The standard definition of efficiency is due to Pareto-Koopman (Gutiérrez-Nieto et al. 2007), which states that "the performance of an entity is efficient if and only if it is not possible to improve any input or output without worsening any other input or output" (Cooper, Seiford, & Tone, 2006). However, according to Debreu-Farrell's definition, "a score of unity indicates technical efficiency because no equiproportionate input reduction is feasible, while a score less than unity indicates the severity of technical inefficiency" (Knox Lovell, 1993).

In this study, sample Decision-Making units' (DMUs) performance is analyzed by measuring the technical efficiency of a particular group of firms. The methodology adopted identifies what type of economies of scale they require to be fully efficient, which is "the optimal use of resources to achieve certain ends" (Abbas et al., 2016). Hence, a DMU's performance depends on its achievement of given objectives.

Different methods to measure MFIs' efficiency

Efficiency is determined by the way MFIs allocate their assets, staff members, and subsidies, to generate the maximum possible output which, in this context, can be measured as, for example, in terms of the number of loans, poverty outreach, or self-sufficiency (Balkenhol, 2007). Non-parametric methods frequently used to measure efficiency include the Data Envelopment Analysis (DEA), free-disposal hull, and the distribution-free approaches. In general terms, they consist on the calculation of efficiency scores with reference to the existing distance between an observation and the frontier of best performing observations (Abbas et al., 2016). That frontier represents a production possibility containing input-output correspondences (Thanassoulis, 2001). The DEA model can incorporate multiple inputs and outputs, which is desirable in the case of MFIs (Haq et al., 2010). In addition, DEA does not require any assumptions regarding the business processes of MFIs (Azad et al., 2016). Frontier methods, as DEA, are quite popular to measure efficiency of the banking sector (Berger and Humphrey, 1997). For instance, according to Mokhtar, AlHabshi, & Abdullah (2006) who report a revision of 47 bank efficiency studies, DEA is the most widely used technique to measure banks' efficiency.

Additionally, there are two approaches that measure technical efficiency when analyzing financial institutions: the production approach and the intermediation approach (Alinsunurin, 2014). In the first approach, the financial institution uses labour and capital, to produce different services and products (loans and deposits). The second approach considers the financial institution to be an intermediary that collects deposits and loanable funds to lend them in order to gain some profits (Gebremichael & Gessesse, 2016). In the former case, deposits are outputs of the firm, while in the latter, deposits are inputs to produce loans (Wijesiri et al., 2015). Considering that the main function of MFIs is to provide loans to those who cannot get them from other financial institutions, the production approach is preferred in this study.

Efficiency of MFIs and banks

A number of studies have used the methods described above to evaluate the efficiency of banks and MFIs, and to make comparative analyses of the results. Some studies have analyzed if a given category of MFIs (i.e. formal MFIs, which include: bank-MFIs, non-bank financial institutions, MFIs, and cooperative-MFIs; semi-formal MFIs include: NGO-MFIs) is more efficient than the others (e.g., Alinsunurin, 2014; Haq, Skully, & Pathan, 2010; Fall et al., 2018; Gebremichael & Gessesse, 2016; Gutiérrez-Nieto et al., 2007; Servin, Lensink, & van den Berg, n.d.; Shan & Akram, 2016; Widiarto & Emrouznejad,2015; Wijesiri, Viganò, & Meoli, 2015; Piot-Lepetit & Tchakoute Tchuigoua, 2021). Some of them find that cooperative-MFIs are more efficient while other studies, depending on the approach adopted, find that bank MFIs are more efficient (Haq et al., 2010; Hassan & Sanchez, 2009; Gutiérrez-Nieto et al., 2007). Under the intermediation approach, bank-MFIs are more efficient; but under the production approach NGO-MFIs are more efficient (Haq, Skully, & Pathan, 2010). Those results make sense because only banks can obtain deposits from their clients given that banks are more regulated. However, when assuming that both types of entities perform the same activities (e.g., provide loans), NGOs turn out to be the more efficient.

Shan & Akram (2016) found that non-profit MFIs are more efficient, at least during a financial crisis. Piot-Lepetit & Tchakoute Tchuigoua (2021) found a similar result when comparing privatelyowned MFIs versus NGOs, the latter show a higher efficiency just after the 2008 crisis. However, when the comparison was made only between NGOs and non-NGOs, the latter turned out to be more financially efficient than the former (Alinsunurin, 2014), and this could be due to the fact that the output variables do not consider qualitative data (like the number of active borrowers, for example). But when that variable is the only output in the model, NGOs are more efficient, meaning that they are consistent with their social objective. Annim (2012) argues there is a trade-off between the MFIs' social objectives and their financial efficiency, and that there is complementarity between the external environment (credit information, property rights and financial development) and MFIs' social efficiency. The empirical results show that efficient MFIs, in terms of their financial performance, fail to reach out to poorer segments of population and, in contrast, efficient MFIs, in terms of social performance, reach out to poorer members of society. Servin, Lensink, & van den Berg (2012) report empirical evidence on the relationship between ownership and technical efficiency of MFIs in Latin America that suggests that technical efficiency, both intra- and interfirm, can be explained by differences in ownership, which is supported by Piot-Lepetit and Tchakoute Tchuigoua's (2021) results.

D'Espallier et al. (2013) examine how unsubsidized institutions (i.e. for-profit MFIs) cope with their social mission and find that the lack of subsidies worsens MFIs' social performances. They also report that strategies to achieve financial self-sufficiency are substantially different across regions. To compensate for non-subsidization, African and Asian MFIs collect more onerous interest rates from their customers. Unsubsidized MFIs in Eastern Europe and Central Asia target less poor clients; and Latin American MFIs reduce the proportion of female borrowers in their portfolio. Though, apparently more regulations also hamper the social efficiency of MFIs (Zainal, et al., 2020).

The findings of the different studies may be influenced by the characteristics of the analyzed sample, for example, differences in the time span covered by each one of them. Some studies analyze one-year periods, while others analyze two or more years. For example, in Haq, Skully & Pathan's (2010) study, when the analysis is performed only with 2004 data, cooperative-MFIs are the most efficient. In contrast, Servin, Lensink, & van den Berg's (2012) study find that for-profit MFIs are more efficient, when analyzing a period from 2003 to 2009, but doing a similar analysis though only considering the last two years (2008-2009), non-profit MFIs are more efficient (Shan & Akram, 2016).

Comparative efficiency studies differ on their selection of the types of financial intermediaries. Possible combinations include MFIs-NGOs with non-NGOs; for-profit MFIs with not-for-profit MFIs, and other combinations that include almost all types of MFIs. What until now has not been reported in the literature are comparisons between MFIs that become publicly listed and other types of MFIs (Fehr & Hishigsuren, 2006).

Research design and methodology

This work's original contribution consists of studying the characteristics, behaviour and functioning of publicly listed MFIs, and comparing their efficiency with other two types of financial intermediaries (non-public MFIs, and public commercial banks). Until now, public MFIs have only been studied in reports about their IPO processes (Cull, Demirgüç-Kunt, & Morduch, 2009; Ashta & Hudon, 2012; Rosenberg, 2007; Chen, Rasmussen, Reille, & Rozas, 2010). Another significant contribution of this work refers to the construction of a global sample of public and non-public MFIs with observations for a relatively long period of time. That constructed sample will be empirically analyzed to respond the following two research questions:

1) Are publicly listed MFIs more efficient than private MFIs?

The process that firms go through in an Initial Public Offering (IPO) is long and expensive. Among other important opportunity costs, firms sacrifice their privacy because regulations force them to reveal their financial information and relevant events to the general public. That fact probably explains why firms that would otherwise be ready to list their stock publicly are unwilling to do so even when they miss the opportunity to obtain cheaper funding (Swanson, 2008). Therefore it is not so common to find MFIs listed in Stock Exchanges. So, this question intends to study the efficiency of those publicly listed MFIs and evaluate if it was worth giving that step compared to non-public MFIs.

A number of studies have studied efficiency in commercial banks (e.g., Abbas, Azid, & Hj Besar, 2016; Abbas, Hammad, Elshahat, & Azid, 2015; Rahman, & Rosman, 2013). Other studies have compared state-owned banks with private banks (e.g., Chen & Yeh, 2000; Ulas & Keskin, 2015; Ataullah, Cockerill, & Le, 2004; Usman, Wang, Mahmood, & Shahid, 2010). However, an extensive literature review did not identify any studies that compare the performance of publicly listed MFIs, with that of listed commercial banks.

Therefore, the second research question is:

2) How efficient are listed MFIs compared to listed commercial banks?

This question narrows the sample to publicly traded MFIs, and their comparable (in size and geographical location) commercial banks. While the clients targeted by both types of entities are usually different, both fulfill the role of financial services providers, and are committed to maximizing their shareholders' wealth.

To approach both research questions, the DEA methodology will be used. It consists on calculating the relative efficiency of DMUs, and setting a benchmark, which represents an efficient frontier. What a DEA does is to envelope DMUs' efficiency observations to identify a frontier that represents the performances of all the DMUs (Cooper, Seiford, & Tone, 2006). When a DMU is operating on the frontier, one can say it is technically efficient (Farrell, 1957). DMUs must have efficiency scores equal to 1 and slacks equal to zero in order to be efficient (Cooper, Seiford, & Tone, 2006). If only the efficient score equals 1, the DMU is known to be "radial", "technical" or "weak" efficient. But if its score is 1 and the slacks are 0, that DMU is "strongly" efficient (Ji & Lee, 2010). Slacks[3] indicate by how much should each DMU increase or decrease each variable in order to be in the efficient frontier in a Pareto way (i.e. without worsening any input or output). This is because the relative efficiency is computed according to the following formula:

$$\text{relative efficiency} = \frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}} \tag{1}$$

Charnes, Cooper, and Rhodes (1978) formulated the linear programming to optimize the formula through a model known as CCR, which assumes constant returns to scale (CRS). An efficient DMU operating under the CRS assumption is technologically efficient but also "uses the most efficient scale of operation" (Casu & Girardone, 2002). However, this assumption is only appropriate when all DMUs are operating at an optimal scale. An alternative model known as BCC includes variable returns to scale (VRS). With this model the overall technical efficiency can be divided into scale and pure technical efficiency. Scale efficiency basically states the degree of deviation from the long-run competitive equilibrium (Yildirim, 2002). Therefore, if both CRS and VRS DEA are conducted and the corresponding efficiency scores of a DMU are different, then that DMU has scale inefficiency. Hence, the VRS specification allows calculating a technical efficiency that is free of scale efficiency effects (Coelli T. , 1996). In this study, the choice is precisely the VRS specification because the main interest is the evaluation of pure technical efficiency of the sample DMUs.

So far, technical efficiency has been explained assuming that the objective is to reduce inputs in order to make inefficient DMUs become efficient units. This is known as the input-oriented model. But when the goal is to maximize the outputs, the technical efficiency is computed using an output-oriented measure. In this study, the selected model is the input-oriented one, because the type of variables used as inputs can be more easily modified by the DMU's managers. In other words, managers seek, given the technology and the already defined product, the best combination of inputs.

[3] This study computes a DEA model based on the Debreu-Farrell definition, which implies that a score of unity means technical efficiency without adjusting for slacks.

Having all the models defined, the freeware known as DEAP is used to compute the efficiency scores. DEAP allows choosing between CRS or VRS, input- or output-oriented models, and to define the number of inputs, outputs, and firms to be analyzed.

The database of DMUs for the present study was integrated with information obtained from S&P Capital IQ, MIX Market, and studies from CGAP. As the original goal of microfinance is to help people living in poverty, and because MFIs first appeared in those places where poverty is a significant problem, the sample only includes institutions from developing countries. Table 1 presents the type of DMUs analyzed and classified by region and country. The region with the largest number of DMUs is Africa, with 23 DMUs; while Eastern Europe and Central Asia is the region with the lowest number of DMUs, with only 6 institutions. The countries with the most DMUs are Nigeria and Indonesia, both with 9 firms; and those with the fewest institutions are Thailand, Azerbaijan, and Bolivia. In total, 19 private MFIs, 16 public MFIs, and 46 listed commercial banks, which add up to 81 DMUs, are used in the following analysis.

To be included in this sample, MFIs must have quarterly financial statements. The sample was expanded to include listed commercial banks with assets from 58 million to 8 billion USDs, the same range of the sample MFIs' assets. As commercial banks are leading entities in the financial sector of any country, and because they have been part of that sector during more time than MFIs, the sample of commercial banks is larger.

Table 1
DMUs per regions, country and type

Regions	**Country**	**Private MFIs**	**Public MFIs**	**Listed commercial banks**	**TOTAL**
Africa	Kenya	1	1	6	8
	Nigeria	0	2	7	9
	South Africa	1	2	0	3
	Tanzania	0	2	1	3
East Asia / Pacific	China	4	0	0	4
	Indonesia	2	2	5	9
	Philippines	0	0	3	3
	Thailand	0	0	1	1
Eastern Europe / Central Asia	Azerbaijan	1	0	0	1
	Ukraine	1	1	3	5
Latin America	Bolivia	1	0	0	1
	Colombia	1	0	1	2
	Mexico	2	1	2	5
	Peru	3	3	1	7
South Asia	Bangladesh	0	1	5	6
	India	0	0	3	3
	Pakistan	0	1	3	4
	Sri Lanka	2	0	5	7
TOTAL		19	16	46	81

Source: Prepared by the authors, based on the analysis of the sample

The variables to be used as inputs and outputs were selected by studying which variables are more frequently used in the financial intermediaries' efficiency literature. A review of 20 studies whose goals include empirical comparisons of the efficiency of different types of financial institutions, how efficiency changes through time, or to identify its determinants (e.g., Abbas, Azid, & Hj Besar, 2016; Haq, Skully, & Pathan, 2010; Alinsunurin, 2014; Van Damme, Wijesiri, & Meoli, 2016; Servin, Lensink & van den Berg, 2012; Kumar & Sensarma, 2017; Gebremichael & Gessesse, 2016; Khan & Gulati, 2021), resulted in a list of the most frequently used variables, as presented in Table 2, below.

Table 2
Inputs and outputs found in the literature

Inputs	**# of times used in the literature**	**Outputs**	**# of times used in the literature**
Operating/administrative expenses	16	Gross loan portfolio	9
Employee	15	Financial revenue	8
Total assets	9	Number of loans outstanding	7
Equity	5	Number of women borrowers	5
Fixed assets	3	Number of active borrowers	5
Deposits	3	Return on assets (ROA)	3
Cost per borrower	3	Number of borrowers per staff member	3
Portfolio at Risk 30 days	1	Investment and other earnings assets	3
Number of offices	1	Number of poorest reached	3
Financial expense	1	Other income	2
Financial cost ratio	1	Number of savers (depositors) per staff member	2
Cost per saver	1	Markup interest income	2
Cost per loan	1	Net savings	1
		Net operating income	1

Source: Prepared by the authors

Many of those variables could be retrieved from the financial statements of each firm. However, not all firms had data for all these variables. So, input and output variables were finally chosen to maximize the number of firms in the sample (see Table 3). The input variables required by DMUs to perform their main activity include: funds, expenses, capital, and equipment, all necessary to provide loans to their clients. Conversely, output variables are the outcome of transforming those inputs, including: loans, profits (losses), yields, and investments.

Table 3
Inputs and outputs used in the analysis

Inputs	Outputs
Operating expense	Gross loan portfolio
Total assets	Interest income
Equity	Total revenue
Fixed assets	Return on assets (ROA)
Interest expense	Total investments
	Operating income
	Return on equity (ROE)

Source: Prepared by the authors

The database contains data from the first quarter of 2009 to the last quarter of 2017. The number of DMUs changes by quarters, according to data availability. The sample of DMUs grew over time, maybe because at a global level MFIs became more open to share their financial data, or to the fact that more MFIs and/or commercial banks went public.

According to Cooper, Seiford, and Tone (2006), a rule of thumb of the DEA model states that $n \geq \max[x * y, 3 * (x + y)]$ where n is the number of DMUs, x represents the number inputs, and y the number of outputs. Notwithstanding, Cook, Tone and Zhu (2014) argue that such rule is mainly imposed by convenience, not by statistical theory. In any case, given that in this analysis the number of inputs is five and the number of outputs is seven, the required number of DMUs must be equal to or greater than 36, which is met in almost all of the quarters in the sample (see Figure 1).

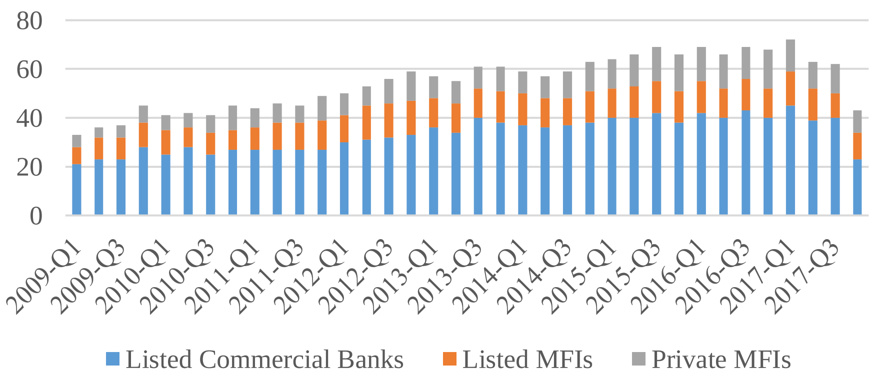

Figure 1. Number of DMUs per quarter.
Source: Elaborated with data from the database used in this research.

DEA results and interpretation

To work with DEA, the data needs to be transformed because of the non-negativity assumption of the methodology. Given the nature of the variables used as outputs (i.e. profits or losses), five out of seven output variables have negative values, hence all output variables are transformed by adding to them the absolute value of the minimum value of all the sample (Cooper et al., 2006). The translation invariance of the VRS model is restricted (i.e., using the original data or the transformed data yields the same optimal solution) (Pastor & Ruiz, 2007). The model is translation invariant on inputs if the output-oriented measure is used, or it is translation invariant on outputs if the input-oriented approach is followed (Portela, Thanassoulis, & Simpson, 2004; Bowlin, 1998). In this study, the input-oriented approach is used. Table 4 shows the descriptive statistics of the data before and after their translation. The pooled sample includes 1,972 observations. As input variables data are not transformed, their descriptive statistics remain the same before and after the data transformation. Though, before the data transformation, the output variables: interest income, total revenue, ROA, operating income, and ROE have negative values. Operating income has the lowest minimum value of all the variables, with a value of -452; hence, in order to make it (and all other negative values) positive, 452.01 is added to the whole sample of output variables.

Therefore, now with the transformation 0.01 is the minimum value of operating income. The variables that have the greatest values are total assets, gross loans, and investments. Return variables (i.e. ROA and ROE) have the lowest values, even after the transformation, since they are ratios.

Table 4
Descriptive statistics

			Before data transformation				After data transformation			
Variable	**Units**	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Inputs										
Operating expense	Millions of USD	1,972	34.25	0.94	0.09	317.40	34.25	0.94	0.09	317.40
Total Assets	Millions of USD	1,972	3,045.99	112.39	2.44	86,614.50	3,045.42	112.39	2.44	86,614.50
Equity	Millions of USD	1,972	373.70	11.33	1.89	4,886.79	373.72	11.33	1.89	4,886.79
Fixed assets	Millions of USD	1,972	64.69	2.16	0.07	1,301.89	64.70	2.16	0.07	1,301.89
Interest expense	Millions of USD	1,972	32.67	1.44	0.002	2,051.17	32.67	1.44	0.002	2,051.17
Outputs										
Gross loan portfolio	Millions of USD	1,972	1,871.40	60.14	0.06	55,016.95	2,322.46	2,669.69	452.01	55,468.96
Interest income	Millions of USD	1,972	76.26	2.45	-75.90	2,409.05	528.23	108.66	376.11	2,861.06
Total revenue	Millions of USD	1,972	50.89	1.50	-434.20	492.23	502.87	66.75	17.81	944.24
ROA	Ratio	1,972	0.01	0.001	-0.87	0.17	452.02	0.04	451.14	452.18
Total Investments	Millions of USD	1,972	662.50	47.58	0.002	44,908.11	1,114.17	2,111.92	452.01	45,360.12
Operating income	Millions of USD	1,972	17.05	0.73	-452.00	270.23	469.05	32.52	0.01	722.24
ROE	Ratio	1,972	0.09	0.02	-27.57	0.85	452.10	0.68	424.44	452.86

Source: Prepared by the authors, based on the analysis of the sample

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The transformed data is used to compute the technical efficiency scores for each DMU individually, considering its main inputs and outputs, as well as those of the other DMUs. In order to have a quarterly technical efficiency score per DMU type, the average value for each DMU group is computed and presented for comparison in Table 5.

The table shows the mean efficiency scores per quarter[4] for each type of financial institution and for the whole sample. The highest scores per quarter, for each type of efficiency are highlighted in the table. For example, in Q1 2009, private MFIs have their scores highlighted, because these ones are the highest compared to those of the other DMU types. The same happened in Q2 2009, but additionally the VRS efficiency score of listed MFIs is highlighted because it is equally high as private MFIs' score. From 2009 to 2011, it is common to find that listed and private MFIs are the more efficient DMUs, particularly when using VRS. Moreover, their scores are equal to 1, which means that they lie on the efficient frontier (i.e., they are pure technically efficient).

Afterwards the mean efficiency of all DMUs decreased dramatically. In 2012 scores of the CRS efficiency are in average 0.10, this means that DMUs could reduce about 90% of their inputs in order to get the same level of outputs. This dismal performance was probably associated with the fact that in 2012 the whole financial industry experienced a severe downturn. During the following years the efficiency scores recovered, especially the scale efficiency, and reached mean values of 0.76 in 2017. This means that DMUs improved their returns to scale. Nonetheless, when considering all the DMUs, the pure technical efficiency (VRS) scores are quite low (though still higher than those of CRS), not even reaching 0.50 efficiency levels, which means that these financial institutions are less than half as efficient as they should be.

[4] In Q1 2015 and Q4 2016 efficiency scores could not be obtained because the DEAP software was unable to find convergence.

Table 5
Mean efficiency scores

	Listed Commercial Banks			Listed MFIs			Private MFIs			All DMUs		
Quarter	**CRS**	**VRS**	**Scale**	**CRS**	**VRS**	**Scale**	**CRS**	**VRS**	**Scale**	**CRS**	**VRS**	**Scale**
2009 Q1	0.617	0.944	0.650	0.694	0.945	0.718	0.921	0.982	0.933	0.679	0.950	0.707
2009 Q2	0.605	0.956	0.631	0.826	1.000	0.826	0.997	1.000	0.997	0.704	0.972	0.720
2009 Q3	0.711	0.955	0.743	0.784	1.000	0.784	0.997	1.000	0.997	0.767	0.972	0.787
2009 Q4	0.686	0.974	0.702	0.870	1.000	0.870	0.890	1.000	0.890	0.758	0.984	0.768
2010 Q1	0.708	0.948	0.740	0.941	1.000	0.941	1.000	1.000	1.000	0.807	0.968	0.827
2010 Q2	0.723	0.965	0.748	1.000	1.000	1.000	1.000	1.000	1.000	0.815	0.977	0.832
2010 Q3	0.792	0.984	0.803	0.985	1.000	0.985	0.974	1.000	0.974	0.865	0.990	0.872
2010 Q4	0.601	0.960	0.619	0.974	1.000	0.974	0.617	0.980	0.620	0.671	0.972	0.682
2011 Q1	0.607	0.967	0.629	0.881	1.000	0.881	0.634	1.000	0.634	0.668	0.980	0.682
2011 Q2	0.636	0.970	0.651	0.882	1.000	0.882	0.632	1.000	0.632	0.694	0.982	0.703
2011 Q3	0.651	0.975	0.661	0.879	1.000	0.879	0.715	0.998	0.715	0.716	0.985	0.723
2011 Q4	0.515	0.712	0.628	0.695	0.898	0.772	0.412	0.804	0.557	0.538	0.777	0.649
2012 Q1	0.061	0.258	0.370	0.069	0.534	0.229	0.260	0.461	0.615	0.099	0.355	0.383
2012 Q2	0.065	0.243	0.417	0.119	0.534	0.322	0.070	0.474	0.247	0.080	0.355	0.366
2012 Q3	0.064	0.219	0.438	0.126	0.539	0.375	0.148	0.394	0.506	0.095	0.330	0.434
2012 Q4	0.077	0.226	0.541	0.217	0.506	0.572	0.221	0.400	0.646	0.139	0.328	0.570
2013 Q1	0.109	0.314	0.445	0.193	0.613	0.319	0.291	0.524	0.538	0.155	0.410	0.433
2013 Q2	0.145	0.336	0.589	0.194	0.580	0.510	0.288	0.435	0.700	0.179	0.405	0.590
2013 Q3	0.120	0.323	0.487	0.185	0.516	0.452	0.389	0.585	0.692	0.172	0.400	0.511
2013 Q4	0.093	0.268	0.521	0.181	0.498	0.533	0.265	0.385	0.656	0.140	0.336	0.546
2014 Q1	0.122	0.262	0.559	0.199	0.541	0.477	0.324	0.467	0.691	0.170	0.355	0.561
2014 Q2	0.103	0.277	0.496	0.216	0.610	0.382	0.367	0.490	0.726	0.168	0.381	0.508
2014 Q3	0.101	0.247	0.556	0.191	0.526	0.371	0.263	0.474	0.650	0.148	0.342	0.539
2014 Q4	0.124	0.200	0.694	0.245	0.488	0.643	0.265	0.433	0.694	0.176	0.303	0.683
2015 Q1												
2015 Q2	0.107	0.239	0.564	0.274	0.501	0.589	0.271	0.511	0.561	0.172	0.344	0.569
2015 Q3	0.118	0.168	0.679	0.260	0.486	0.564	0.264	0.570	0.614	0.174	0.309	0.644
2015 Q4	0.129	0.209	0.650	0.216	0.536	0.562	0.281	0.510	0.654	0.181	0.342	0.634
2016 Q1	0.120	0.164	0.662	0.202	0.368	0.619	0.249	0.463	0.636	0.162	0.263	0.649
2016 Q2	0.102	0.156	0.649	0.195	0.411	0.503	0.242	0.477	0.600	0.149	0.271	0.612
2016 Q3	0.113	0.197	0.665	0.212	0.566	0.531	0.237	0.532	0.637	0.155	0.330	0.634
2016 Q4												
2017 Q1	0.225	0.244	0.947	0.323	0.480	0.721	0.327	0.408	0.863	0.263	0.320	0.888
2017 Q2	0.202	0.236	0.929	0.343	0.639	0.578	0.417	0.518	0.824	0.269	0.369	0.838
2017 Q3	0.192	0.277	0.747	0.354	0.601	0.512	0.302	0.496	0.671	0.239	0.372	0.695
2017 Q4	0.282	0.428	0.607	0.329	0.592	0.599	0.432	0.634	0.688	0.326	0.513	0.622

Source: Prepared by the authors, based on the analysis of the sample

To compare the efficiency of different types of DMUs and determine which are more efficient, a Kruskal-Wallis (1952) test is performed. This is a non-parametric test that determines if there is a significant difference between groups. The null hypothesis is that the mean ranks of the sub-samples are the same. Table 6 shows the H statistic of each type of efficiency.

Table 6
Kruskal-Wallis test

Efficiency type	**H statistic**	
CRS	12.518	
VRS	18.406	
Scale	4.932	**
Critical value (99%)	9.210	
Critical value (95%)	5.991	
Critical value (90%)	4.605	

*, **, *** significance at 10%, 5% and 1% levels, respectively.
Source: Prepared by the authors

The statistics for CRS and VRS are not significant, so the null hypothesis is rejected. Hence, the mean CRS and VRS efficiency scores of the three types of DMUs studied are different. In the case of scale efficiency, the H statistic is significant at the 5% level, which suggests that the mean scale efficiencies of the three types of DMUs are the same; therefore there is no need to make a comparison among them. Nonetheless, as two out of the three types of efficiency scores are statistically different between them, a comparison of the three is presented. After confirming that the mean efficiency scores are indeed different, the remaining question left is: which type of financial institution is more efficient? To answer it, a comparison of efficiency scores is made.

Through all the sample period, commercial banks never had the highest score for CRS and VRS. However, they had the highest scores in scale efficiency only in nine quarters. Private MFIs' efficiency scores are the highest (in all categories) in 2009 and in the first semester of 2010. From 2012 to 2014, the CRS and scale efficiency scores of these institutions are the highest; except for Q2 2012 that none of them were the highest. From 2015 to 2016, private MFIs also had the highest scores for CRS, except in two quarters (Q2 2015 and Q3 2017). Also, during that period but only in Q4 of 2015 and 2017, private MFIs had the highest scores in scale efficiency. This type of institutions was the most technically efficient in Q1 2009 and Q4 2017.

It is interesting to see how mean efficiency scores vary widely through time. In Q1 2009, the efficiency score for CRS is 0.92, for VRS is 0.98, and for scale efficiency is 0.93; in Q4 2017, efficiency scores are 0.43, 0.63, and 0.68 for CRS, VRS, and scale efficiency, respectively. The latter suggests that DMUs are becoming less efficient. For instance, private MFIs were efficient at a 90% level during 2009. But in 2017, those same institutions are only efficient at a 40%-60% level, which means they are using around 50% more of their inputs than they should. The story is not too different for the other institutions. Listed MFIs also had high efficiency scores during the first three years of the analysis, which were close to 1 and above 87%. Consistently listed MFIs had the highest efficiency scores for VRS from 2009 to 2014, except for Q1 2009 and Q3 2013, but with lower scores (~52% of efficiency). In 2010 and 2011 (except Q1 2010) they were the most technically efficient (i.e., they had the highest scores in all types of efficiencies). Lastly, for the first three quarters of 2017, again listed MFIs had the highest efficiency.

Because the results vary a lot through time, Table 7 shows the frequency that a given type of DMU is more efficient. Panel A shows the frequency each individual DMU type has the highest efficiency score. Panel B reports the frequency when several DMU types have the highest efficiency scores. Panel C combines both previous panels. For example, listed MFIs and private MFIs both have the highest efficiency scores in eight quarters, and this number is sum up to the number of times each has the highest score individually.

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Results show that commercial banks turn out to be the most efficient only in scale efficiency in nine quarters out of 34 possible outcomes. Listed MFIs are more pure-technically efficient (VRS) in 27 quarters out of 34, while they are the most efficient in 10 quarters according to the CRS measure and in 8 quarters according to scale efficiency. Private MFIs are more technically efficient (CRS), as they presented the highest efficiency scores in 25 quarters, while they are more scale efficient in 19 quarters and more pure technical efficient in 15.

These results suggest that private MFIs are more efficient only when assuming that they are operating at an optimal scale, i.e., they are not affected by imperfect competition or subject to constraints in their finances. However, in reality, markets are quite connected and usually firms are impacted by what happens to the industry they belong to, therefore the need to segregate CRS into its components. When only considering VRS, the conclusion is that in the period from 2009 to 2017, listed MFIs are more efficient than their counterparts. As the DEA is a deterministic model, a statistical significance cannot be computed between the CRS and the VRS efficiencies in order to identify which one is more significant. Though the significance mainly relies on the activities each DMU perform and type of efficiency that should be really monitored. Nonetheless, the economic significance of this study is that the MFIs are more efficient than commercial banks when analyzing the most relevant variables used as indicators by the financial intermediaries.

Table 7
Quantification of the most efficient DMUs

Panel A. *Number of times each DMU has the highest efficiency score*

	CRS TE	VRS TE	Scale
Listed commercial banks			8
Listed MFIs	9	19	7
Private MFIs	24	7	17

Panel B. *Number of times a DMU has the highest efficiency score alongside other DMU*

	CRS TE	VRS TE	Scale
Listed commercial banks			1
Listed MFIs	1	8	1
Private MFIs	1	8	2

Panel C. *Total number of times each DMU has the highest efficiency score*

	CRS TE	VRS TE	Scale
Listed commercial banks			9
Listed MFIs	10	27	8
Private MFIs	25	15	19

Source: Prepared by the authors, based on the analysis of the sample

Conclusion

This study contributes to the existing literature in several ways. First, the sample used in this analysis includes a pool that includes both private and publicly listed MFIs. The sample is complemented by matching listed commercial banks from the same geographical location. The construction of the database represented a significant effort of data search in multiple sources, the homologation of the retrieved information and the arrangement of the data for analytical treatment. Second, while it is relatively common to find studies on MFIs from a given country, this study's sample includes financial institutions from different developing countries around the globe. As a matter of fact that highlights this study's comprehensiveness: all the world's geographic regions are represented. Third, although several studies analyze the efficiency of private MFIs, this is the first project that examines the efficiency of listed MFIs. Usually MFIs or banks are segmented by ownership type (i.e. state-owned or domestic-private), location (i.e. regional or national), or formality (i.e. formal: bank MFIs, non-bank financial institution MFIs and cooperative MFIs; semi-formal MFIs: NGO-MFIs). This study makes a mix of those categories and treats the sample as either private or publicly traded MFIs. The results' evidence indicates that publicly listed MFIs are more efficient than private MFIs when these are not assumed to operate at an optimal scale. It can be concluded that listed MFIs must focus on improving their scale of operation so as to minimize their costs, whereas private MFIs must strengthen their processes and foster best practices to improve their performance.

Lastly, the results obtained with DEA shed light on the performance of the microfinance industry in relation to commercial banks. Systemically, banks underperformed in every efficiency measure. A striking fact is found: comparable public commercial banks are inefficient compared to MFIs. It is empirically proved the existence of alternative business models that are more efficient than the traditional banking intermediation system and at the same time can alleviate the necessity to overcome financial exclusion. Regulators and policymakers should make a priority in their agendas to boost the microfinance industry, as the proven efficiency of the MFIs might translate into better services to the poor and to microbusinesses.

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