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Is there an optimal microcredit size to maximize the social and financial efficiencies of microfinance institutions?

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A B S T R A C T

Financial intermediation theory posits that a smaller loan size triggers a higher cost per dollar lent. This leads to question whether microfinance can become a self-sustainable industry. Hence, in microfinance innovations like loans without collateral, progressive loans, solidarity groups and relational lending are employed to reduce asymmetric information costs, adverse selection, and moral hazard while serving the poorest people. Crucially, we find a non-linear U-shaped effect of loan size on financial and social efficiencies. This reconciles the two opposite strands of the literature, aligning microfinance and banking central principles. The major implication of this study is that, unlike banking, microfinance institutions can grant small size loans while simultaneously obtaining high levels of financial and social efficiency. Indeed, our findings do not support the widely debated *mission drift* assumption since loan size does not generate a trade-off between financial and social outcomes. Therefore, loan size is a core management variable.

1. Introduction

Microfinance is a financial paradigm of development economics, which ultimately aims to alleviate poverty. This goal is why microfinance institutions (MFIs) provide microcredit to people from the bottom of the socio-economic pyramid (BoP): low-income people, rural populations, women, and ethnic minorities, among others. The primary purpose of these institutions is to fund small businesses that may generate income to improve the borrowers' living conditions. Hence, due to the nature of the social business activity, MFIs face two theoretically conflicting objectives, the so-called *double bottom line* or *dual mission* (Morduch, 2000): to provide access to financial services to the poorest people and attain financial sustainability.

Nonetheless, during the last years, academic and practitioner observers posit that many MFIs have prioritized financial goals over social objectives (Quayes, 2020). This focus on the financial outcomes has mostly guaranteed the survival of MFIs due to the radical slowdown of the funds contributed by the governments and donors (Nourani et al., 2021), who historically have covered all the financial needs of the majority of the MFIs (Galema et al., 2011).

Accordingly, the current challenge facing the microfinance industry is to accomplish MFIs having high-efficiency levels in both the social and financial fields. In other words, as Hermes et al. (2011) stated, in an optimal situation, MFIs should serve many (i.e., a high

Abbreviations: MFI, Microfinance Institution; BoP, Bottom of the socio-economic Pyramid; DEA, Data Envelopment Analysis; GLP, Gross Loan Portfolio; VIF, Variance Inflation Factor; HHI, Herfindahl–Hirschman index; GDP, Gross Domestic Product; GFC, Global Financial Crisis; GMM, Generalized Method of Moments.

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breadth of outreach) poor (i.e., a great depth of outreach) individuals and, simultaneously, be financially sustainable.

Nevertheless, whether social and financial objectives can be concurrently attained is still an open research question that researchers continue debating intensively (Quayes, 2020; Reichert, 2018). Consequently, analyzing the loan size's impact on the social and financial outcomes of MFIs should be a leading objective for the microfinance sector. On the one hand, part of the literature posits that since the screening, monitoring, and enforcement costs are fixed for a loan or an applicant, a smaller loan size results in a higher cost per dollar lent (Copestake, 2007; Hermes et al., 2011; Hudon, 2010; Morduch, 2000). On the other hand, other research sustains that, by lending small loans, MFIs can reduce their unitary lending costs due to decreased asymmetric information costs, adverse selection, and moral hazard (Woolcock, 2001). The asymmetric information costs may be reduced since granting smaller loans lets MFIs continuously monitor borrowers and offer progressively higher-sized loans after timely repayments (Egli, 2004), which enables MFIs to use *relationship banking* (Boot and Thakor, 2000). Indeed, the relational lending approach is the basis on which lies the successful business model of the microfinance industry since it, as Berger and Udell (2002) argued, "enables us to acquire information over time through contact with the borrowers and its local community on a variety of dimensions and use this information in their decisions about the availability and terms of loans." Indeed, microfinance is considered a true-intensive lending activity based on the social capital of those borrowers (that is, the negative impact that the loan default causes on their personal reputation and social standing) with whom loan officers establish close interpersonal relationships to screen and discipline them (Blanco-Oliver et al., 2021).

Despite the leading role of loan size in the microfinance sector, to date, its effect on the efficiency of MFIs has received little attention; therefore, this paper aims to fill this gap by analyzing the effect of the microcredit size on the social and financial efficiencies of MFIs. This study uses a panel dataset with information for 679 MFIs from 90 countries to perform a two-stage analysis. The first stage uses data envelopment analysis (DEA) to rank the MFIs according to their technical efficiency score. The second stage applies a panel Tobit regression to analyze the effect of the microcredit size on the (social and financial) efficiency of MFIs.

This study contributes to the existing research by documenting a nonlinear U-shaped relationship between the loan size and the financial and social efficiency of the MFIs, reconciling the two confronted strands of the literature. Until now, microfinance and banking research remained firmly entrenched in opposite theoretical and empirical grounds, which align with this paper's findings. More importantly, from the management point of view, we highlight that the controversial and widely debated mission drift assumption does not work in microfinance, and, thus, managers of MFIs can keep on granting small-size loans while simultaneously obtaining high levels of financial and social outcomes. Specifically, we find that managers of MFIs should avoid loan sizes in the (un) optimal range and aim at granting larger or smaller loans with the highest financial and social efficiency levels. These findings enhance the role of loan size as a critical variable for managing MFIs and that under both the "*welfarist*" and "*institutionalist*" approaches, MFIs can have a high social impact while being financially efficient.

The paper proceeds as follows. Section 2 provides an overview of the literature on the factors that may affect the financial and social outcomes of MFIs. Section 3 describes the data and the methodology applied, while Section 4 discusses the main results and the robustness tests conducted. Finally, Section 5 concludes by showing our study's practical and theoretical implications.

2. Background and hypotheses

The dual mission of MFIs requires implementing management strategies that allow balancing both financial and social goals to guarantee their long-term survival while accomplishing the primary objective of microfinance: to finance the poorest of the poor.

Following the theory of financial intermediation, the smaller loans have higher unitary operational fixed costs per dollar lent, caused by the costs related to the corporate structure and administrative management, screening, monitoring, and enforcing, which are independent of the microcredit size. Consequently, granting small loans can reduce the financial efficiency of MFIs. Moreover, from a credit risk point of view, other arguments also arise, suggesting that smaller loans negatively impact the financial outcomes of MFIs. In this vein, very small loans are mostly granted to the poorest credit applicants without credit records and economic guarantees (asset collaterals), who are more vulnerable to macroeconomic shocks due to their small business size and strong dependence on agricultural activities (Dercon and Krishnan, 2000; Quayes, 2012). In contrast, borrowers with business experience and economic collaterals may face adverse economic situations skillfully. Consequently, lending small microcredit increases MFIs' problems of asymmetry information and credit risk (and thus, default losses) substantially, resulting in lower levels of financial efficiency. Thus, we state our first hypothesis:

Hypothesis 1. *(H_1): The larger the microcredit, the higher the financial efficiency of the MFI.*

Still, a more extensive theoretical analysis of the effect of the loan size on the financial efficiency of the MFIs may reveal that both variables may also be negatively related. In this sense, the financial feasibility is based on reducing the information costs and the problems of asymmetry information. These problems are substantially higher in developing countries and for small firms due to the greater lack of credit bureaus and other external sources of information on borrowers' behavior (Ruiz et al., 2023), as customary in microfinance. Therefore, in microfinance, the loans are guaranteed by the debtor's social capital (Ansari et al., 2012); that is, there are no financial collaterals (Lindvert et al., 2017). Indeed, within the microfinance environment, a common belief is that financial transactions are highly trust-intensive (Duarte et al., 2012). This feature explains why microfinance is considered a time-consuming lending industry since it usually provides borrowers with financial services, business training, and mentoring advice.

In practice, MFIs implement a relationship lending approach by encouraging group lending and interpersonal relationships between loan officers and borrowers to understand the local networks and creditworthiness (Woolcock, 2001). Group lending is one of the essential novelties engendered by the "Grameen Model," where the loan groups assume the majority of the screening, monitoring, and enforcement costs. Indeed, rather than the banks, these groups determine who will be better borrowers, make sure that the group members use the funds wisely, and impose sanctions if they refuse to repay. As Feigenberg et al. (2013) found, solidarity group lending decreases the MFI's default risk. Accordingly, given that under the relationship lending approach, MFIs increase the collection of very soft information about borrowers (mainly, the unique information available) and, consequently, reduce their credit risk and default losses, it is possible to state that in microfinance, unlike in the traditional banking sector, granting very small loans may become a financially efficient lending activity.

Thus, other theoretical arguments justify an adverse effect of the loan size on the financial outcomes of MFIs. First, the smaller the microcredit is, the lower the default losses caused by non-repayment due to the lower credit exposure are. Note that the loan size is directly related to the loss-given default, which is the amount of money a lending intermediary loses when a borrower defaults on a loan (Mason, 2014). Second, lower-size loans are usually granted to solidarity loan groups in which the debtors' social capital is used as collateral, and a "social penalty" can be imposed on individuals who do not meet their commitments (Paal and Wiseman, 2011; Quidt et al., 2016). Third, female applicants often receive smaller microcredit (Agier and Szafarz, 2013a). In practice, MFIs focus on serving female customers to improve their corporate reputation (since serving the female population is considered a valuable social performance indicator) and increase their financial outcomes due to the higher repayment rates associated with female borrowers (d'Espallier et al., 2011).

The above arguments suggest that lending (very) small loans to the poorest people can lead to financially feasible lending activity. Although this statement seemingly goes against Hypothesis 1 (H_1), it shows that loan size and financial efficiency likely follow a nonlinear relationship. The microfinance literature has not deeply analyzed the nonlinear effects of loan size on efficiency; however, these effects have been recently found in financial research. For instance, Jahmane and Gaies (2020) show that corporate social responsibility and corporate financial performance are related using a U-shaped function. Accordingly, our second hypothesis states.

Hypothesis 2. *(H_2): The microcredit size and the financial efficiency of MFIs are related through a nonlinear U-shaped function.*

Regarding the social performance of MFIs, the first issue to highlight is that there is no consensus in the literature about measuring the social outcomes of MFIs (Quayes and Joseph, 2021); however, it seems reasonable to think that reaching those population segments with fewer resources and development opportunities is the fundamental pillar on which the social commitment of the microfinance programs must be built. Thus, MFIs focused on serving poor women, rural populations, and ethnic minorities are considered high-social-impact organizations. In this vein, the average loan size per borrower has been widely used in microfinance research to measure the social performance of MFIs. The loan size is used as a proxy for the applicants' poverty level because, in most cases, small loans can only lead to uncompetitive and vulnerable businesses, often generating low incomes. It is customary in traditional lending organizations to grant larger loans to those applicants with higher creditworthiness (Berger et al., 2014). These credit applicants are not the target market of microfinance programs because they often obtain funding in the commercial banking credit market (Chakrabarty and Bass, 2014a; b). Therefore, given that the poorest population mostly requests smaller loans, we assume a negative relationship exists between the loan size and the social performance of the MFIs.

Furthermore, Agier and Szafarz (2013b) demonstrate that there is a loan size gender gap since female applicants receive smaller loans than their male counterparts under similar conditions. In other words, the loan size is dependent on the gender of the borrower. This result is in line with the findings of previous research, which document that two types of gender bias exist in the lending markets: the first is caused by stricter lending criteria (Quigley and Patel, 2022), and the second is linked to worse lending conditions (Cozarenco and Szafarz, 2018). The causes of this gender discrimination should be sought mainly in the sociocultural and institutional framework. Note that granting lower loan sizes to female borrowers favors the sociocultural acceptance of the subordinate role of the female population. Indeed, women have historically faced sociocultural prejudices as they are considered to have weaker entrepreneurial skills (Ibañez and Guerrero, 2021; Wheadon and Duval-Couetil, 2019). In this vein, religious and cultural norms that prevent women from benefiting from their social capital partially cause female discrimination in the credit market (Oppedal Berge, Garcia Pires, 2020). Accordingly, this argument also supports our presumption of smaller loans being related to a greater social performance of MFIs. Thereby, based on the previous rationalization, our third hypothesis posits that.

Hypothesis 3. *(H_3): The larger the size of the microcredit, the lower the social efficiency of the MFI.*

To further unpick the loan-size effect on the social efficiency of MFIs, we also test the existence of a potential nonlinear relationship between both. Unlike the arguments postulated by the traditional banking logic, the backbone of the microfinance industry sustains that people with greater socio-economic exclusion and poverty situations are those with higher repayment rates because MFIs have developed procedures and strategies that enable them to serve BoP people (mainly the female and rural populations) and simultaneously decrease default losses. These procedures include (i) joint liability contracts (also known as solidarity group lending schemes) under which all group members assume the credit risk of each loan, preventing MFIs from incurring losses due to microcredit default. (ii) Progressive lending with recurring payments (often weekly) enables MFIs to increase the number of contacts with the borrowers and extract useful information from them, planning frequent meetings with a group of borrowers to be monitored, screened, mentored, and trained with tips on business management. (iii) Using social capital as loan collateral is a powerful disincentive to avoid loan default (Lindvert et al., 2017).

Definitively, these lending strategies clearly show strategic support for implementing the relational lending approach as a successful business model in microfinance since it decreases the credit risk associated with the poorest people. Indeed, the relational lending strategy works better in rural areas and the female population, where there is often more societal pressure on credit applicants (Blanco-Oliver and Irimia-Diéguez, 2021). Note that in the more economically depressed environments, social capital becomes women's capital due to the more significant impact of social barriers on gender roles. In this vein, the leading role played by women in the family and the community develops their capability of successfully building and maintaining strong networks that ultimately increase loan repayments (Janssens, 2010). The above arguments, therefore, support that using a relational banking system and its associated set of lending policies enables reducing the asymmetric information problems faced by MFIs and, thus, their credit risk. Accordingly, MFIs would be more incentivized to grant a higher loan size to credit applicants with the lowest credit risk levels. Therefore, we expect that, in contrast to H_3, the loan size and social performance of MFIs would be positively related, leading to testing the existence of a U-shaped relationship between the loan size and social efficiency of MFIs. Thus, we propose our fourth hypothesis:

Hypothesis 4. *(H_4): The loan size and the social efficiency of MFIs are related through a nonlinear U-shaped function.*

3. Data and methodology

3.1. Sample description

This paper's dataset was built by collecting information from three data sources. First, the data on MFIs were collected from the Microfinance Information Exchange (MIX Market), a worldwide information platform containing financial and operational information on MFIs. Second, country-level macroeconomic data, the institutional quality framework, and governance indicators were extracted from the World Bank databases.

After selecting only cases from MFIs with audited data, excluding outliers, and the panel data sample according to the inputs and outputs variables used in the first-stage analysis (DEA), we used a data set with 2335 observations from 679 MFIs for 11 years from 2008 to 2018. Our sample includes information on MFIs from six geographical regions (and 90 countries) around the world, strengthening the international dimension of our research. Table 1 provides the summary statistics for the variables used in this study, and Appendix A (Table A.1) presents the correlation matrix of these variables.

3.2. Methodology

3.2.1. First-stage DEA efficiency estimate

As mentioned, this study performs a two-stage analysis, which has been widely used by the microfinance literature (Fall et al., 2018). In the first stage, the MFI efficiency scores are estimated by using DEA, first proposed by Farrell (1957) and improved by Charnes et al. (1978) and Banker et al. (1984). In contrast to parametric efficiency models (such as stochastic frontier analysis), DEA is

Table 1
Summary of descriptive statistics.

Panel A: Variables used in DEA (first stage)					
	Mean	Std. dev.	Median	Min.	Max.
Input variables:					
Total assets (USD million)	64	140	18	0.14	2000
Number employees	496.62	775.12	190	10	6472
Operating expenses (USD million)	6.90	13	2.40	0.02	100
Output variables:					
Financial income (USD million)	13	26	4.10	0.06	240
Rural gross loan portfolio (USD million)	22	50	5.90	0.006	880
Number of women borrowers	50,632	100,000	11,906	25	850,000
Panel B: Variables used in the truncated regressions (second stage)					
	Mean	Std. dev.	Median	Min.	Max.
Dependent variables:					
Financial efficiency score	0.5551	0.1622	0.5591	0.1340	1
Social efficiency score	0.3417	0.2278	0.3212	0.0012	1
Independent variables:					
Loan size (log)	6.52	1.08	6.58	4.62	8.70
Number of active borrowers (log)	9.97	1.59	9.86	3.97	13.68
Debt to equity ratio	3.99	2.71	3.51	0.31	13.86
Return on assets	0.02	0.05	0.02	− 0.25	0.18
Operational self-sufficiency	1.15	0.21	1.13	0.02	2.15
Operating expense on assets	0.16	0.09	0.14	0.03	0.66
Portfolio at risk (more than 30 days)	0.05	0.08	0.03	0	0.95
Z-score	19.50	17.39	13.95	0.05	99.33
Bank dummy	0.12	0.32	0	0	1
NGO dummy	0.34	0.47	0	0	1
Latin-American dummy	0.37	0.48	0	0	1
HHI (log)	7.69	0.75	7.63	6.40	9.21
The institutional context	− 0.52	0.35	− 0.54	− 1.86	1.17
Unemployment rate	6.33	5.87	4.42	0.14	47.50
GDP per capita (log)	7.83	0.84	7.80	5.40	9.90
Inflation	5.61	4.21	4.91	− 6.81	36.91
Rural population	50.50	19.43	50.69	4.95	89.36
Crisis	0.47	0.50	0	0	1

a non-parametric method that does not impose a specific structure on the shape of the efficient frontier, representing its main advantage (Drake et al., 2006).

Thereby, DEA analysis enables assessing an MFI's performance relative to a "best practice" frontier (Farrell, 1957). Essentially, by comparing peers, this method ranks the lending organizations from higher to lower efficiency scores, allowing the optimal situation to be defined as a minimization input or a maximization output problem.

This paper employs an input-oriented DEA model (we presume that the managers of MFIs have more control over inputs than over outputs) with both constant and variable returns to scale, as developed by Banker et al. (1984). This model provides an efficiency score for n number of DMUs by using m outputs and s inputs, as presented below:

$$\theta = \max_{u,y} \frac{\sum_{r=1}^{s} \mu_r y_{ro}}{\sum_{j=1}^{m} v_j x_{jo}} \tag{1}$$

subject to,

$$\frac{\sum_{r=1}^{s} \mu_r y_{ri}}{\sum_{j=1}^{m} v_j x_{ji}} \leq 1, i = 1, 2, \ldots, n$$

$$\mu_r > 0, v_j > 0, for \quad all \quad r, j$$

where the j DMU consumes x_{ji} inputs to produce y_{ri} outputs, μ_r and v_j being the weights of the outputs and inputs, respectively, which must be > 0 (Cooper et al., 2011). The technical efficiency measures are ranked between 0 and 1, taking a value of 1 if the DMUs located on the production frontier, indicating the most efficient observations.

The selection of financial intermediaries' inputs and outputs is controversial and determines the efficiency model approach (production or intermediation) followed (Berger and Humphrey, 1991). The main dispute between these approaches is how they classify deposits; the former views deposits as outputs, while the latter considers deposits as input variables. Our study follows the production approach since most MFIs are not allowed to collect deposits; hence, the intermediation approach cannot be applied. In addition, as Bikker and Bos (2008) suggested, the production approach is the reference method for lenders with low autonomy in credit policy, as in the case of MFIs.

Based on these considerations, we carry out two efficiency models in which the inputs are primarily used in the banking and microfinance literature (Servin et al., 2012), and the outputs are different for each model. Separately, we measure the financial and social efficiency levels, as shown in Table 1, following previous studies (Gutiérrez-Nieto et al., 2009; Servin et al., 2012; Efendic and Hadziahmetovic, 2017). Note that the gross loan portfolio (GLP) of an MFI must be equal to the number of active borrowers of this entity multiplied by the size of each outstanding microcredit. Thus, the GLP is a social variable since it measures the magnitude of an MFI's scope on the population; it can also be considered a business ratio because it reflects MFI's commercial success and size. Therefore, we use the rural GLP in which the social aspect is strengthened more than the total GLP, given that the rural population is considered a relevant socio-economic exclusion factor (Khavul et al., 2013). In other words, the inclusion of the rural GLP as an output penalizes, in terms of social efficiency, those MFIs with a relatively large market share but not focused on rural areas.

3.2.2. Second-stage truncated regression

In the second stage, we run a set of regressions where the dependent variable is the efficiency score obtained from the DEA models. This two-stage approach is theoretically justified by Banker and Natarajan (2008), who state that a DEA model followed by a maximum likelihood estimation yields a consistent estimator that performs at least as well as parametric models in the estimation of the effect of the contextual factors on the efficiency measures. Nevertheless, as Greene (2003) stated, ordinary least square regression makes biased and inconsistent estimations with censored dependent variables. Accordingly, since the efficiency scores from the first-stage analysis have a censored structure—i.e., limited to [0,1]—in this second-stage analysis, we apply panel Tobit regression with the maximum likelihood estimation method for parameter estimations. Furthermore, according to Fernández-Val and Weidner (2016), we perform a random effect estimation Tobit regression because the use of fixed effects analysis causes unexpected parameter problems and biased outcomes.

Therefore, we consider the following general panel data in the Tobit model:

$$y_{i,t}^{*} = \beta_0 + \beta_1 \quad ALS_{i,t} + \beta_i \quad X_{i,t} + u_{i,t} \tag{2}$$

$$y_{i,t} = \begin{cases} y_{i,t}^{*}, if \quad y_{i,t}^{*} < 1 \\ 1, otherwise \end{cases} \quad i = 1, \ldots, N \quad and \quad t = 1, \ldots, T$$

The i subscript denotes the cross-sectional dimension, and t is the time-series dimension. The dependent variable, y_{it}, is the efficiency score obtained from the DEA, ALS_{it} is the average loan size, measured by using the average loan balance per borrower (gross loan portfolio/number of active borrowers), X_{it} is the vector of the control variables of an MFI i at time t, and u_{it} is the error term.

The matrix of the control variables (X_{it}) includes two types of variables. First, it incorporates MFI-specific variables, such as size, productivity, credit risk, insolvency risk, leverage, profitability, level of operational self-sustainability, profit orientation, ownership structure, and each country's level of competition in the microfinance market. Given that microfinance is a social industry, to measure the size of MFIs, we use the natural logarithm of the number of active borrowers served, which is also considered a social impact variable. The greater the population funded by MFIs, the greater the breadth of its outreach. As a productivity control variable, the rate of operating expenses divided by assets is included, while the credit risk supported by MFI is measured using the percentage of the loan portfolio that is overdue for more than 30 days (Bogan, 2012; Gutiérrez-Nieto et al., 2009; Mersland and Strøm, 2010). We also include the return on assets (ROA)-based Z-scores widely used to measure the financial intermediaries' probability of insolvency (insolvency risk) (Ashraf, 2017; Lepetit and Strobel, 2015). Following most of the existing literature (Bermpei et al., 2018), we calculate the MFI Z-score by the sum of an MFI's ROA and the capital-to-assets ratio over the standard deviation of its ROA (sdROA): Z-score = $\frac{ROA+CAR}{sdROA}$. Note that the Z-score measures the distance from insolvency as it represents the number of standard deviations that an MFI's ROA has to fall for the MFI to become insolvent (Demirgüç-Kunt and Huizinga, 2010). Leverage, profitability, and operational sustainability capture critical dimensions of business organizations and are also controlled by well-known ratios: debt to equity ratio, ROA, and operational self-sufficiency of MFIs, respectively. Operational self-sufficiency measures the ability of MFIs to generate revenues higher than their costs. Being self-sufficient enables MFIs to develop their original mission (that is, to fund the poorest people) without depending on donations; hence, the self-sufficiency of MFIs is a crucial variable for the long-term survival of these lending organizations. A control variable by profit orientation and ownership structure is also considered since the organizational performance is strongly affected by the corporate governance structures and owners' fiscal incentives (Blanco-Oliver and Irimia-Diéguez, 2021).

Table 2
Effect of loan size on the efficiency of microfinance institutions.

	Linear relationship		Nonlinear relationship	
Dependent variable:	(1) Financial efficiency	(2) Social efficiency	(3) Financial efficiency	(4) Social efficiency
Loan size (log)	0.0112*	– 0.0637***	– 0.1425***	– 0.3695***
	(0.0058)	(0.0084)	(0.0450)	(0.0645)
Loan size^2 (log)			0.0115***	0.0229***
			(0.0033)	(0.0048)
Number of active borrowers (log)	0.0155***	0.0138***	0.0148***	0.0123***
	(0.0029)	(0.0044)	(0.0029)	(0.0044)
Debt to equity ratio	0.0024	0.0006	0.0018	– 0.0003
	(0.0015)	(0.0022)	(0.0015)	(0.0022)
Return on assets	0.9094***	– 0.1530	0.9301***	– 0.1136
	(0.1472)	(0.2011)	(0.1470)	(0.2003)
Operational self-sufficiency	0.0803**	0.0853**	0.0819**	0.0887**
	(0.0317)	(0.0432)	(0.0317)	(0.0430)
Operating expense on assets	0.3351***	– 0.6787***	0.3473***	– 0.6525***
	(0.0550)	(0.0780)	(0.0550)	(0.0781)
Portfolio at risk (more than 30 days)	0.4550***	– 0.0527	0.4652***	– 0.0347
	(0.0472)	(0.0656)	(0.0472)	(0.0655)
Z-score	– 0.0006**	– 0.0003	– 0.0006***	– 0.0004
	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Bank dummy	– 0.0007	– 0.1061***	0.0003	– 0.1044***
	(0.0141)	(0.0215)	(0.0141)	(0.0216)
NGO dummy	– 0.0270***	– 0.0300**	– 0.0287***	– 0.0335**
	(0.0099)	(0.0149)	(0.0099)	(0.0150)
Latin-American dummy	– 0.0286**	0.0894***	– 0.0214*	0.1039***
	(0.0128)	(0.0194)	(0.0130)	(0.0197)
HHI (log)	– 0.0370***	– 0.0153**	– 0.0329***	– 0.0074
	(0.0054)	(0.0076)	(0.0055)	(0.0078)
The institutional context	– 0.0061	0.0217	– 0.0102	0.0129
	(0.0136)	(0.0200)	(0.0137)	(0.0201)
Unemployment rate	– 0.0000	0.0047***	0.0005	0.0059***
	(0.0009)	(0.0014)	(0.0010)	(0.0014)
GDP per capita (log)	0.0282***	0.0549***	0.0255***	0.0493***
	(0.0086)	(0.0130)	(0.0087)	(0.0131)
Inflation	– 0.0101***	– 0.0022**	– 0.0104***	– 0.0027***
	(0.0008)	(0.0011)	(0.0008)	(0.0011)
Rural population	– 0.0005	0.0048***	– 0.0006	0.0046***
	(0.0005)	(0.0007)	(0.0005)	(0.0007)
Crisis	– 0.0106*	– 0.0152*	– 0.0103*	– 0.0154*
	(0.0061)	(0.0082)	(0.0061)	(0.0082)
Year dummies	yes	yes	yes	yes
Number of observations	2335	2335	2335	2335
Number of MFIs	679	679	679	679
Wald-chi^2	684.60***	405.81***	698.16***	428.44***

Note: * = $p < 0.10$, ** = $p < 0.05$, and *** = $p < 0.01$. Clustered robust standard errors in parentheses.

Finally, we also controlled the competition level faced by MFIs using the Herfindahl–Hirschman index (HHI) in terms of total assets; HHI is widely used as a concentration sector indicator (Shim, 2019) and is calculated as the sum of square percentages of total assets of all MFIs annually in each country.

Second, country-level variables are also included to capture the institutional context of the country where an MFI operates since, as Chortareas et al. (2013) found, financial institutions operating under more developed institutional and sociocultural frameworks are more likely to achieve higher efficiency levels. Indeed, as suggested by Bermpei et al. (2018), institutional quality contributes to a properly functioning credit market by reducing adverse selection, borrower moral hazard, and loan default risk. To capture the macroeconomic environment, we introduce as control variables the gross domestic product (GDP) per capita and the unemployment and inflation rates. Additionally, we incorporate a dummy variable, which takes the value 1 during the period 2008–2012 and 0 otherwise, to consider the impact that the Global Financial Crisis (GFC) had on the microfinance market. Moreover, following previous research (Uddin et al., 2020), we capture the institutional quality by using the worldwide governance indicator based on six dimensions of governance, including voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, the rule of law, and control of corruption. Finally, since MFIs operating in Latin America have unique features (Aggarwal et al., 2015), we introduce a dummy variable that takes a value of 1 when the MFI operates in Latin America and

Table 3
Effect of loan size on *the inefficiency* of microfinance institutions.

	Linear relationship		Nonlinear relationship	
Dependent variable:	(1) Financial *in*efficiency	(2) Social *in*efficiency	(3) Financial *in*efficiency	(4) Social *in*efficiency
Financial *in*efficiency $_{(-1)}$	− 0.1563***		− 0.0945***	
	(0.0259)		(0.0161)	
Social *in*efficiency $_{(-1)}$		0.3289**		− 0.7567***
		(0.1383)		(0.0421)
Loan size (log)	− 0.3087***	12.4163***	1.8861**	39.9952***
	(0.1162)	(3.3936)	(0.8849)	(8.7764)
Loan size^2 (log)			− 0.1516**	− 3.0492***
			(0.0637)	(0.6734)
Number of active borrowers (log)	− 0.0910**	− 0.3887	− 0.0323	− 2.6466***
	(0.0411)	(0.9733)	(0.0261)	(0.4811)
Debt to equity ratio	− 0.0392*	2.9530***	− 0.0151	1.4435***
	(0.0200)	(1.0947)	(0.0148)	(0.4087)
Return on assets	5.9429	62.9662**	− 1.7020	− 28.2932
	(4.5953)	(30.9448)	(3.1462)	(22.0500)
Operational self-sufficiency	− 3.1490***	11.2406	− 1.8721**	7.8931**
	(1.0756)	(7.8096)	(0.8234)	(3.7580)
Operating expense on assets	− 5.2556***	80.5528***	− 1.1452	14.8443*
	(0.8598)	(19.4650)	(1.1826)	(8.4178)
Portfolio at risk (more than 30 days)	− 0.6954	154.5619**	− 6.6417***	− 2.1626
	(0.5735)	(67.0631)	(1.2191)	(1.5305)
Z-score	− 0.0117	0.1159*	0.0025	0.0820***
	(0.0092)	(0.0609)	(0.0022)	(0.0307)
Bank dummy	0.3583*	3.5201	− 0.0676	8.9250***
	(0.2129)	(4.8551)	(0.1081)	(1.9782)
NGO dummy	0.5424	15.0238	− 0.0311	− 2.0868*
	(0.5209)	(9.9068)	(0.0888)	(1.1523)
Latin-American dummy	− 0.5993	− 4.5964	− 0.2791*	− 9.9200***
	(0.5035)	(4.5222)	(0.1550)	(2.0808)
HHI (log)	0.1332	0.9554	0.1123*	− 0.1583
	(0.1012)	(3.2249)	(0.0600)	(0.8146)
The institutional context	− 0.1408	38.0372***	− 0.3648	6.5055*
	(0.1453)	(10.8983)	(0.3262)	(3.9235)
Unemployment rate	− 0.0249	− 0.3051	− 0.0239	− 0.2129**
	(0.0173)	(0.2652)	(0.0171)	(0.1037)
GDP per capita (log)	0.1173*	− 5.1782**	0.0710	− 7.5980***
	(0.0703)	(2.5173)	(0.0823)	(2.6292)
Inflation	− 0.0270**	3.2729***	− 0.0059	0.1078
	(0.0120)	(0.5255)	(0.0081)	(0.0923)
Rural population	− 0.0088	0.1962	− 0.0009	− 0.4654***
	(0.0105)	(0.1315)	(0.0043)	(0.0977)
Crisis	0.1577**	− 1.7351	0.0682*	6.1802***
	(0.0685)	(1.5602)	(0.0393)	(0.5500)
Year dummies	yes	yes	yes	yes
Number of observations	1758	1758	1758	1758
Number of MFIs	584	584	584	584
Arellano–Bond test for AR(2) correlation (*p*-value)	0.379	0.296	0.400	0.645
Sargan test of overidentification (*p*-value)	0.786	0.993	1.000	0.979

Note: * = $p < 0.10$, ** = $p < 0.05$, and *** = $p < 0.01$. Clustered robust standard errors in parentheses. (−1) denotes the previous year's value.

Table 4
Robustness check—Results of bootstrap-truncated regressions.

Dependent variable:	(1) Financial efficiency	(2) Social efficiency
Loan size (log)	− 0.0966***	− 0.3355***
	(0.0375)	(0.0900)
Loan size^2 (log)	0.0085***	0.0185***
	(0.0028)	(0.0067)
Number of active borrowers (log)	0.0150***	0.0155***
	(0.0023)	(0.0053)
Debt to equity ratio	0.0021	− 0.0032
	(0.0013)	(0.0032)
Return on assets	1.0112***	0.2084
	(0.1454)	(0.3664)
Operational self-sufficiency	0.0820***	0.0803
	(0.0310)	(0.0748)
Operating expense on assets	0.4125***	− 1.1393***
	(0.0458)	(0.1293)
Portfolio at risk (more than 30 days)	0.3969***	− 0.2161*
	(0.0441)	(0.1141)
Z-score	− 0.0004**	− 0.0012***
	(0.0002)	(0.0004)
Bank dummy	0.0015	− 0.2189***
	(0.0100)	(0.0280)
NGO dummy	− 0.0177**	− 0.0627***
	(0.0073)	(0.0177)
Latin-American dummy	− 0.0164*	0.1856***
	(0.0098)	(0.0255)
HHI (log)	− 0.0277***	− 0.0134
	(0.0049)	(0.0119)
The institutional context	− 0.0126	0.0044
	(0.0113)	(0.0265)
Unemployment rate	0.0002	0.0076***
	(0.0007)	(0.0017)
GDP per capita (log)	0.0322***	0.1206***
	(0.0063)	(0.0167)
Inflation	− 0.0073***	− 0.0065***
	(0.0008)	(0.0019)
Rural population	− 0.0001	0.0098***
	(0.0003)	(0.0009)
Crisis	− 0.016^{2}***	0.0006
	(0.0059)	(0.0153)
Number of observations	2323	2323
Number of MFIs	679	679
Wald-chi^2	713.94***	374.31***

Note: * = $p < 0.10$, ** = $p < 0.05$, and *** = $p < 0.01$. Clustered robust standard errors are in parentheses; the total number of iterations is 2000.

0 otherwise.

Furthermore, we explore another sort of regression since the efficiency score obtained by an MFI will likely be affected by previous efficiency levels. In other words, our model considers an inter-temporal effect due to the efficiency at time *t* being dependent on the efficiency at time $t - 1$. Accordingly, we re-estimated the model by introducing the lagged efficiency score as an independent variable. Moreover, we also deal with the serial correlation and potential omission of control variables (selection bias) problems. To better account for the possibility of lagged effects, serial correlation, and selection bias, we adopted (two steps) the Arellano–Bond dynamic panel data model generalized method of moments (GMM) estimator (Windmeijer, 2005), *xtabond2*. Using GMM allows us to handle a possible contemporaneous correlation of the errors (i.e., being correlated across firms within the same period) and heteroscedasticity (i.e., having unequal variances across different subsets of MFIs). Note that error terms may not be independent among different periods in a panel data design, resulting in a possible serial correlation problem (Hicks, 1994), indicating that for each MFI, the association between independent and dependent variables in the last year of analysis could be driven by (or at least be correlated with) the relationship between variables in the previous year. Hence, through GMM, we also obtained estimations with lagged-dependent variables as controls.

Furthermore, since our dependent variable (efficiency score) is limited in the range [0,1], following Banker et al. (2010), we calculate an inefficiency measure through the inversed proportion of efficiency ratios; therefore, it is possible to conduct a GMM estimation while keeping the rank provided by DEA analysis. Accordingly, we also specify the following GMM regression for the second-stage estimation:

$$y^*_{i,t} = \beta_0 + \beta_1 \quad y^*_{i,t-1} + \beta_2 \quad ALS_{i,t} + \beta_i \quad X_{i,t} + u_{i,t} \tag{3}$$

4. Results and discussion

4.1. Main results

The first set of regressions focuses on studying the loan size's effect on the financial and social efficiencies of MFIs. Table 2 shows that our findings reveal a positive impact of the loan size on financial efficiency, which confirms H_1. Conversely, supporting H_3, we find that loan size and social efficiency are negatively related.

These results are in line with the reasoning of the traditional banking industry and suggest that (very) small loans do not generate financially efficient operations but do make a strong social impact because they are granted mainly to vulnerable people; hence, we show that the loan size influences the financial and social outcomes of MFIs, although in opposite directions. Indeed, a priori, our findings suggest that, based on the loan size, there is a trade-off between the financial and social efficiencies of MFIs.

Nonetheless, as explained in the hypotheses section, to fully understand the impact of the loan size on the MFIś financial and social efficiency, the potential nonlinear relationships between the average loan size and the efficiency scores have also been tested (H_2 and H_4). In this sense, a nonlinear effect may explain the opposite results found by the literature regarding the relationship between the financial and social performances of MFIs.

Table 2 (nonlinear models) suggests that the loan size and the financial efficiency of MFIs are related through a U-shaped function. This result confirms H_2 and, surprisingly, consolidates the divergent findings shown by the extant literature and settles a research question that, to date, has been intensively debated by academics and practitioners. Thus, this finding resolves the controversy between microfinance and traditional banking approaches about whether microfinance can become a financially profitable and self-sustaining lending industry. On the one hand, our results suggest that the traditional banking logic, which posits that (very) small loans generate higher fixed costs per dollar lent and, thus, cannot produce financially efficient lending programs, does not work in microfinance. Our results highlight the singularity of the microfinance sector. Indeed, our findings support that the innovative loan configurations used by MFIs (such as loans without financial collateral, social capital, the reputation of borrowers as a substitute for financial collateral, progressive loan structures with short amortization terms, regular repayment, solidarity group lending, and relational lending) reduce the asymmetric information costs, adverse selection, and moral hazard while serving the poorest people with (very) small loans. This finding aligns with the "*welfarist approach*" of microfinance that advocates that, unlike the commercial banking vision, MFIs do not need to move away from their original social objective to become financially profitable. Therefore, the mission drift is unjustified as MFIs can deal efficiently with their dual missions.

On the other hand, this U-shaped relationship also shows that granting larger loan sizes increases a lender's financial efficiency. This result aligns with the traditional banking point of view that sustains that larger loans reduce the fixed costs per dollar lent. This finding does not contradict the microfinance paradigm since poorer borrowers usually have no access to large amounts of money.

Similarly, we also find a nonlinear U-shaped effect of the loan size on the social efficiency of MFIs, thus confirming H_4. Accordingly, our results show that small loans are associated with high social impact and larger loan sizes, which is mainly explained by the lower credit risk faced by MFIs when focusing on serving the female and rural population, which allows these lenders to fund these two target markets and simultaneously reach a strong social performance. Crucially, this finding shows again that in microfinance, two alternative business models co-exist, and both have a powerful social commitment. On the one hand, social-oriented MFIs indicate that, by using innovative instruments such as the relational lending approach, progressive loans, and solidarity group lending, they grant (very) small loans to the poorest people. On the other hand, commercial-oriented MFIs also focus on the female and rural populations with a larger loan size since their priority is maximizing their financial performance.

Since we find that the loan size is related to financial and social efficiencies through a nonlinear U-shaped relationship, one can wonder which loan size causes the optimal financial and social efficiency levels. To do so, we calculate for each curve the minimum point, which generates the lowest financial and social efficiency, respectively. MFIs should avoid a loan size around this minimum point and push for larger or smaller loans. Specifically, we find this minimum point to be 503.03 US dollars (USD) (percentile 40.59% of loan-size distribution) for financial efficiency and 705.08 USD (percentile 49.35% of loan-size distribution) for social efficiency. More importantly, in line with the findings of Blanco-Oliver and Irimia-Diéguez (2021), these results highlight that in microfinance, two feasible business models (the "*welfarist approach*" supported by social or non-profit-oriented MFIs, and the "*institutionalist approach*" encouraged by commercial or profit-oriented MFIs) bring about the highest levels for both financial and social outcomes.

Finally, we re-estimate the previous models by including the lagged efficiency score as an independent variable, which allows us to address the inter-temporal effect in our models since the efficiency at time t is dependent on the efficiency at time $t - 1$. At the same time, serial correlation and selection bias problems may arise. To deal with this, as argued in the methodology section, we apply the dynamic GMM estimations, as shown in Table 3. Note that, in this case, the dependent variable is inefficiency, as contended in the methodology section. Table 4 shows that the previous results are confirmed by the GMM regressions, strengthening our findings and their implications.

4.2. Robustness checks

To confirm the previous findings, we make a robustness test using the Simar and Wilson (2007) procedure, which is a two-stage DEA analysis where the DEA scores are first evaluated and then regressed on potential covariates with the use of bootstrapped truncated regression. These authors sustain that using the Tobit regression in the second stage causes explanatory variables to correlate with the error term as inputs and outputs to correlate with explanatory variables. To deal with these potential problems, we follow the

Table A.1
Pearson bivariate correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Loan size	1								
Num: active borrowers	– 0.298***	1							
Debt equity ratio	0.216***	0.196***	1						
Return on asset	– 0.0824***	0.150***	– 0.207***	1					
Operational self-sufficiency	– 0.0182	0.185***	– 0.180***	0.864***	1				
Operating expense assets	– 0.359***	– 0.132***	– 0.325***	– 0.0662**	– 0.247***	1			
PAR30	0.0779***	– 0.148***	0.0321	– 0.278***	– 0.270***	– 0.0340	1		
Z-score	0.134***	– 0.0871***	– 0.160***	0.105***	0.146***	– 0.168***	– 0.0262	1	
Bank dummy	0.156***	0.275***	0.181***	– 0.0438*	– 0.0222	– 0.0973***	– 0.0216	– 0.00509	1
NGO dummy	– 0.433***	– 0.0154	– 0.213***	0.0569**	0.00983	0.238***	0.000420	– 0.0599**	– 0.255***
Latin-American dummy	0.380***	– 0.203***	0.0146	– 0.0865***	– 0.154***	0.0948***	0.0718***	0.148***	0.0603**
HHI	0.0169	– 0.0933***	– 0.222***	0.0392	0.0149	0.246***	0.0191	– 0.139***	– 0.0301
The institutional context	0.141***	– 0.102***	– 0.140***	– 0.0164	– 0.0566**	0.134***	0.0629**	0.0767***	– 0.129***
Unemployment rate	0.141***	– 0.0686***	– 0.188***	0.0327	0.0163	0.0509*	0.0299	– 0.133***	– 0.0384
GDP Per capita	0.475***	– 0.219***	– 0.0658**	0.0417*	– 0.0150	0.0887***	0.0162	0.101***	– 0.00380
Inflation	– 0.279***	0.0517*	0.0239	0.0697***	0.0619**	0.0284	– 0.0264	– 0.100***	0.0683***
Rural population	– 0.455***	0.221***	0.0550**	– 0.00388	0.0943***	– 0.178***	– 0.0530*	– 0.0628**	– 0.0378
Crisis	– 0.101***	– 0.165***	– 0.0260	– 0.0240	– 0.0417*	0.0184	0.0507*	0.0417*	– 0.0342

* = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

recommendations of Simar and Wilson (2007) and implement a double-bootstrapped procedure (Algorithm II) that permits valid inference while simultaneously generating standard errors and confidence intervals for the efficiency estimates.

As Table 4 indicates, the results from Simar and Wilson's (2007) procedure confirm the nonlinear effects of the loan size on the financial and social efficiencies of MFIs; thus, these robustness checks validate our findings.

5. Conclusions

Unlike traditional banking, granting small loans in the microfinance sector has a double benefit for MFIs, (i) reducing the default losses in the case of non-repayment due to the lower credit exposure and (ii) enabling using relationship banking and other innovative lending instruments, such as progressive loans, regular repayments, and solidarity groups, decreasing the information costs while minimizing MFIs' credit risks.

We aim to study the linear and nonlinear effects of the loan size on (separately) the financial and social efficiencies of MFIs. Our analysis is set in microfinance, which is an ideal case study due to the existence of financial and social objectives and the wide use of the microcredit size to measure outreach.

Our results show, first, that the loan size and the financial efficiency of MFIs are related through a U-shaped function. Essentially, our findings suggest that despite the higher fixed costs per dollar lent that the smaller loans generate, this small loan size is compatible with efficient financial lending programs. Following the traditional financial intermediation logic, we also find that larger microcredits increase the financial efficiency of MFIs. This result reconciles the two confronted strands of the literature since, as argued, until now, microfinance and banking research remained firmly entrenched in opposite theoretical and empirical grounds, which align with the findings of this paper.

Second, we also find a nonlinear U-shaped effect of the loan size on the social efficiency of MFIs. Our results suggest that small and large microcredits can trigger high social efficiency levels for MFIs. This conclusion has relevant implications for practitioners and shows the duality of MFIs that operate in the microfinance sector. On the one hand, social-oriented MFIs focus on serving by lending very small microcredits to the most excluded population. On the other hand, commercial-oriented MFIs want to maximize their financial performance by granting large loans yet continue to focus on women and rural borrowers since these are the population segments with higher repayment rates, leading to a greater social reputation.

Based on these findings, the significant implication of this study is that, unlike the banking point of view, MFIs can sustainably operate by lending small loans while simultaneously obtaining high levels of financial and social efficiency. Indeed, our findings do not support the widely debated mission drift of MFIs since the loan size does not generate a trade-off between financial and social outcomes. Crucially, we find that to obtain the highest financial efficiency levels, MFIs should avoid loan sizes between 503.03 USD and 705.08 USD and push for larger or smaller loans than these amounts.

Our findings have relevant implications for scholars and practitioners. From the perspective of the former, our results highlight that more attention should be paid to nonlinear relationships, which may arise in the efficiency analysis of MFIs. This is particularly true regarding loan size -one of the most important variables that characterize the microfinance industry. From a management point of view, the loan size arises as a core variable for managing MFIs. In this sense, despite most MFIs supposing that reaching high financial and social outcomes simultaneously are conflicting objectives, the microcredit size can be used to attain this double bottom line. Accordingly, MFI managers must determine their loan sizes following the financial or social objectives they wish to reach; however, the range 503.03–705.08 USD must be avoided, and they should aim at granting larger or smaller loans, which are what perform the highest financial and social efficiency levels. In other words, our results suggest that small and large loans can lead to the highest

(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	VIF
									3.06
									1.57
									1.52
									4.50
									4.94
									1.91
									1.12
									1.21
									1.26
1									1.44
0.0399	1								2.78
− 0.0250	− 0.258***	1							1.46
0.0237	0.188***	0.253***	1						1.69
− 0.0419*	− 0.179***	0.289***	0.359***	1					1.55
− 0.0584**	0.449***	0.108***	0.505***	0.269***	1				3.09
0.00942	− 0.227***	0.0361	− 0.243***	− 0.115***	− 0.249***	1			1.30
0.000403	− 0.658***	− 0.0704***	− 0.476***	− 0.223***	− 0.786***	0.214***	1		4.54
− 0.0185	− 0.00944	− 0.0440*	− 0.0459*	0.0234	− 0.0791***	0.274***	0.0321	1	1.17

financial and social efficiency levels. More importantly, this finding highlights that in microfinance co-exist two feasible alternative business models (the "*welfarist approach*" supported by social or non-profit-oriented MFIs and the "*institutionalist approach*" encouraged by commercial or profit-oriented MFIs); both perform a powerful social commitment while being financially efficient.

CRediT authorship contribution statement

Blanco-Oliver: Conceptualization, Methodology, Formal analysis, Data curation, Software, Writing - Original draft preparation, Writing- Reviewing and Editing, Visualization. **Irimia-Diéguez**: Conceptualization, Formal analysis, Writing- Original draft, Writing-Reviewing and Editing, Supervision, Visualization, Funding acquisition. **Vázquez-Cueto**: Conceptualization, Methodology, Formal analysis, Data curation, Software, Validation.

Declarations of Competing Interest

None.

Data availability

Data will be made available on request.

Appendix A

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We compute a variance inflation factor (VIF) analysis to deal with potential multicollinearity issues. All resulting VIF values are well under 10, the threshold for assessing multicollinearity (Hair et al., 2010).

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