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Excessive focus on risk? Non-performing loans and efficiency of microfinance institutions

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Abstract

Microfinance is a banking market in which operating costs are high, while non-performing loans (NPLs) rates are low. While the existing literature tends to explain that the high operating costs arise from the provision of small loans, we argue that excessive efforts to control loan losses can also be a contributing factor. Therefore, this article investigates the relationship between NPLs and the cost efficiency of microfinance institutions (MFIs). Using a unique global sample of rated MFIs and applying stochastic frontier analysis together with Granger-causality test and generalized method of moments (GMM), we find, in contrast to positive linear relationship evidence in commercial banking studies, a nonlinear (U-shape) relationship between operating costs and NPLs. This implies that MFIs need to balance their cost efficiency with asset quality.

KEYWORDS

cost efficiency, Granger-causality test, microfinance, non-performing loans, stochastic frontier analysis, system GMM

1 | INTRODUCTION

In this article, we aim to be the first to rigorously study the relationship between non-performing loans (NPLs) and cost efficiency in the global microfinance industry. Modern microfinance emerged in the 1970s as a response to the failures (e.g., high NPLs rates) of state-funded credit programs (Armendáriz & Morduch, 2010; Hulme & Mosley, 1996). Lower NPLs rates have been one of the main achievements and advantages of microfinance over the former credit programs. In fact, NPLs rates in microfinance are lower than those in traditional banking markets (Rosenberg, Gonzalez, & Narain, 2009; Sievers & Vandenberg, 2007).

However, in the ongoing attempt to meet the high demand for credit of micro-enterprises, microfinance institutions (MFIs) failed to pay sufficient attention to their cost efficiency. The main reason for this is that borrowers were willing to pay high interest rates. Given that businesses in the informal economy are normally profitable due to the availability of promising investment opportunities (Armendáriz & Morduch, 2010), the poor are often willing to pay a high price for credit. Based on the principle of diminishing marginal returns to capital, Lucas (1990) shows that Indian borrowers were willing to pay 58 times more interest than American borrowers. As a result, MFIs often pass the cost of lending on to the borrower in the form of high interest. Thus, while NPLs rates are low in microfinance, operating costs are generally high. This suggests a possible trade-off between NPLs and operating costs, and hence offers an interesting research setting.

While banking scholars have long been concerned with the relationship between operating costs and NPLs (e.g., Berger & DeYoung, 1997; Fiordelisi, Marques-Ibanez, & Molyneux, 2011; Hughes & Mester, 1993), we are not aware of similar studies using microfinance data. This omission is unfortunate considering the relationship between the high operating costs and the high interest rates in the industry. Moreover, an overemphasis on risk may lead MFIs to practice too strict credit screening, thus leaving the target clientele unserved (Amin, Rai, & Topa, 2003; Pearlman, 2012).

To cover the high operating costs, MFIs are forced to charge high interest rates on loans (Battilana & Dorado, 2010; Hardy, Holden, & Prokopenko, 2003). There are several examples of MFIs charging 50 and even 100% or more on loans to economically poor individuals. This practice has brought discredit on the microfinance industry (Bateman, 2010; Malkin, 2008). Nevertheless, the high interest rates in microfinance are generally a result not of high profits but of the high costs of delivering microcredit. As shown by Mersland and Strøm (2010), it is not the "hunger for high profits" but the need to cover costs that is the main operating compass of MFIs. Therefore, reducing operating costs means that MFIs' lending rates can be reduced, and poorer segments of the population can be served in a sustainable manner.

Relationship banking theory, which many MFIs practice (Serrano-Cinca & Gutiérrez-Nieto, 2014), suggests a negative relationship between operating costs and NPLs. In relationship banking, more resources are often invested in creating and maintaining ties with clients in the form of more screening and monitoring (Boot, 2000; Diamond, 1991; Petersen & Rajan, 1995). This investment makes the overall operating costs of the financial institution shoot up, while, obviously, repayment rates improve (Puri, Rocholl, & Steffen, 2017), and hence there is a negative relationship between operating costs and NPLs. Moreover, the historical account of microfinance (see Section 2), where cost efficiency was sacrificed for high repayment rates, also suggests a negative relationship.

However, many banking studies show that there is a positive link between NPLs and operating costs (e.g., Berger & DeYoung, 1997; Fiordelisi et al., 2011; Williams, 2004). Berger and DeYoung (1997) outline three reasons for the positive relationship. First, poorly managed banks tend to offer many low-quality loans, which eventually increase the stock of NPLs. Second, skimping on screening costs results in the issuance of poor-quality loans, which leads to more NPLs and more costs to control the NPLs. Third, external exogenous factors cause borrowers to default, which in turn causes the lender to incur extra monitoring costs to curb the NPLs. Since MFIs mirror banks in the services they provide (Armendáriz & Morduch, 2010), one can also expect such a positive relationship in microfinance. Taken together, all these arguments–those for a negative relationship and those for a positive relationship between NPLs and operating costs–suggest the possibility of a nonlinear relationship between cost efficiency and asset quality in microfinance.

We apply a unique, hand-collected global sample based on external rating reports on 607 MFIs operating in 87 countries. Using stochastic frontier analysis together with Granger-causality test and system GMM (generalized method of moments), we find that, indeed, there is a significant relationship between operating costs and NPLs in microfinance. While previous banking studies indicate a linear relationship between inefficiency and NPLs rates, we find a nonlinear, U-shaped relationship. Specifically, our findings show that an increase in NPLs reduces the cost inefficiency of MFIs, but a further increase leads to higher inefficiencies.

An important implication of this result is that microfinance practitioners should consider the trade-off between NPLs and operating costs in order to avoid an overemphasis on asset quality at the expense of cost efficiency. High operating costs are argued by many to be *the* main challenge facing MFIs today (Mersland & Strøm, 2010). Thus, MFIs operating with low NPLs could consider relaxing some of their screening and monitoring efforts in order to reduce their operational costs and potentially include more vulnerable customers. At the same time, MFIs with higher NPLs could put emphasis on reducing such loans in order to help them reduce their operating costs.

The rest of the article is organized as follows. Section 2 reviews the literature and formulates the hypotheses. Section 3 presents the data and describes the econometric methods applied. Section 4 presents the empirical results and Section 5 concludes.

2 | LITERATURE AND HYPOTHESIS DEVELOPMENT

2.1 | Determinants of operating costs

There are many factors influencing the operating costs of MFIs. Such factors may include economies of scale and scope (Hartarska, Shen, & Mersland, 2013), learning and experience, technological advancement (Caudill, Gropper, & Hartarska, 2009), and the operating institutional environment. Economies of scale concern the link between average cost per unit and the number of units produced by a firm (Kwan & Eisenbeis, 1996). The ability to produce in large volumes is associated with cost savings as lower per-unit costs are achieved. Hartarska et al. (2013) prove the existence of economies of scale in the microfinance industry.

Economies of scope are achieved when a financial institution reuses previously gathered customer information as well as infrastructure to generate new revenue without incurring additional costs (Petersen & Rajan, 1994). Such economies are basically concerned with joint production, where the total production cost is less than the sum of individual production costs (Kwan & Eisenbeis, 1996). Delgado, Parmeter, Hartarska, and Mersland (2015) show that most, if not all, MFIs achieve economies of scope when offering clients saving services alongside loans. Learning curve theory suggests that cost efficiency improves over time as a firm repeats its processes and learns from them each time. Caudill et al. (2009) produce evidence to support learning curve theory in the microfinance industry where a group of MFIs becomes more cost effective over time.

In addition, with the introduction of new technologies in production, a bank may improve its cost efficiency level. For instance, new microfinance technologies such as mobile banking and online crowdfunding may help reduce costs and increase MFIs' outreach (Cull, Demirgüç-Kunt, & Morduch, 2009). Furthermore, the costs of financial intermediation can be influenced by banking regulation (Demirguc-Kunt, Laeven, & Levine, 2004). Like banks, some MFIs are regulated by banking authorities (Ledgerwood, 1999) and the costs associated with this regulation are passed on to their clients in the form of higher lending rates (Hardy et al., 2003).

Finally, relationship banking influences the cost of lending when financial intermediaries like MFIs create and maintain ties with their customers over a long period. To create such ties, the financial institution begins by gathering private or "soft" information about the client and such private information is costly to gather (Diamond, 1984). Thus, screening and monitoring costs are often high in the short run, but at the same time intermediation costs decline because of information reusability and lower NPLs, resulting in lower screening and monitoring costs in the long run (Bharath, Dahiya, Saunders, & Srinivasan, 2011; Boot, 2000; Petersen & Rajan, 1994). In sum, relationship banking influences operating costs both positively and negatively.

2.2 | Efficiency and non-performing loans

Hughes and Mester (1993) and Berger and DeYoung (1997), among others, demonstrate how non-performing loans (NPLs) relate to cost efficiency. Hughes and Mester (1993) argue that when a bank fails to invest resources in the initial screening and monitoring of borrowers, the result is lower operating costs in the short run but higher NPLs in the long run. The high NPLs then require more monitoring efforts, leading to high monitoring costs. Berger and DeYoung (1997) refer to this as the "skimping" hypothesis. They further illustrate that bad luck or external factors (e.g., economic downturns), which are beyond the borrowers' control, can cause NPLs resulting in additional costs for the lending institution. These additional costs may relate to factors such as additional monitoring efforts, renegotiations of contract terms, and the efforts of senior management to curb losses on loan (Berger & DeYoung, 1997).

In general, banking studies (e.g., Berger & DeYoung, 1997; Fiordelisi et al., 2011; Kwan & Eisenbeis, 1996) provide evidence for a positive relationship between operating costs and NPLs. Kwan and Eisenbeis (1996) use a stochastic efficient frontier approach to investigate inefficiency of US banking firms in relation to their NPLs. They find that inefficient banks tend to have higher NPLs. Similar findings have been documented by Berger and DeYoung (1997). In a relatively recent study, Fiordelisi et al. (2011) report similar findings to those of Berger and DeYoung (1997).

To the best of our knowledge, empirical evidence on the link between efficiency and NPLs is missing in the microfinance literature. We aim to close this gap. The importance of improving MFIs' cost efficiency has been stressed not only because the high costs jeopardize the overall sustainability of the industry (Cull et al., 2009), but also because the high interest rates impede MFIs' ability to benefit their target customers, the poorest potential clients (Mersland & Strøm, 2010). Thus, the high operating costs of MFIs are actually the main challenge in the industry as well as the main reason for much of the criticism that has been directed at the microfinance industry (Rosenberg et al., 2009).

Equation (1) illustrates why operating costs are the main challenge in microfinance:

$$\text{Profit} = \text{yield} - \text{funding cost} - \text{operating cost} - \text{loan loss}, \tag{1}$$

where *yield* is the interest revenue from the loan portfolio, *funding cost* is the interest expense on borrowings, *operating cost* includes salaries and administrative costs, and *loan loss* represents losses arising from NPLs. Thanks to access to international loans from impact investors (Mersland & Urgeghe, 2013), subsidies (Hudon & Traca, 2011), and low interest on deposits, the finance costs and loan losses of MFIs are generally quite low. As mentioned earlier, loan losses are also low in microfinance. The challenge is the operating costs, which are the main determinant of lending rates in microfinance (Cull et al., 2009).

As Mersland and Strøm (2014) illustrate, operating costs represent about 61% of financial revenue, funding costs 17%, and loan loss provisions only 7%, leaving a profit margin of 15%. This indicates that reducing operating costs could greatly reduce lending rates and improve MFIs' profitability level, which could pave the way for a more sustainable industry. Moreover, high operating costs make it unprofitable to offer small loans to target clientele; thus, reduced operating costs could facilitate MFIs' outreach to poorer clients (Mersland & Strøm, 2010).

Finally, focusing too much on repayment of microcredit has the tendency to drive away the poorest segments of the poor populations, whom MFIs claim to be their target clients. Using data from Peru, Pearlman (2012) shows that because of strict repayment requirements and penalties in microfinance, very poor people have less of a tendency to use microcredit. This finding supports that of Amin et al. (2003) who use data from Bangladesh. Thus, overemphasis on risk has implications on not only the cost efficiency but also the outreach of MFIs. That is, both the sustainability and social objectives of MFIs are affected by too much focus on NPLs.

2.3 | Hypothesis development

Relationship banking theory suggests a negative relationship (trade-off) between operating costs and NPLs. Creating and keeping relationships with clients is costly due to high selection and monitoring costs (Diamond, 1984; Petersen & Rajan, 1994). Since the business model of most MFIs is one of relationship banking with close contact between the loan officer and the client (Dixon, Ritchie, & Siwale, 2007; Serrano-Cinca & Gutiérrez-Nieto, 2014; Siwale & Ritchie, 2012), the low NPLs reported in the industry are a result of the large investments in the screening and monitoring of clients. Puri et al. (2017) find that relationship banking methods result in lower NPLs because of better selection and monitoring of borrowers. Implicitly, the selection and monitoring costs in relationship banking are negatively related to the NPLs. Altunbas, Carbo, Gardener, and Molyneux (2007) find a negative relationship between NPLs and operating costs.

Moreover, the history of microfinance paints a picture of a trade-off between high operating costs and low NPLs. Modern microfinance emerged in the 1970s as a solution to problems associated with development finance institutions (DFIs), which were funded by governments and agencies to provide credit to farmers and other poor people (Hulme & Mosley, 1996; Morduch, 1999). About four decades after the DFI initiatives were launched in the 1930s (Hulme & Mosley, 1996), many studies (e.g., Adams & Graham, 1981; Sanderatne, 1978; World-Bank, 1975) showed that the financial performance of these DFIs had turned out to be unsatisfactory.

For instance, Adams, Graham, and von Pischke (1984, p. 1) described the performance of DFIs as "disappointing," while Thillairajah (1994) claimed that DFIs in Africa had a 100% failure rate! It was shown that high rates of NPLs were a major problem since arrears rates ranged from 55% (e.g., in Ghana) to 95% (e.g., in Nigeria) (Sanderatne, 1978). In short, the average NPLs rate in state-funded credit programs was more than 50% (Hulme & Mosley, 1996; Morduch, 1999).

Microfinance sprang up with innovations to overcome three main problems faced by DFIs. Obviously, one problem was the high NPLs rates; the other two were lack of access to credit for poor people, especially women, and challenges related to screening borrowers without collateral (Hulme & Mosley, 1996). MFIs started to provide small amounts of credit to poor people and micro-enterprises that were excluded from mainstream banking services (Armendáriz & Morduch, 2010). Since its inception, microfinance has been praised worldwide for achieving its primary goal of financial inclusion (Biosca, Lenton, & Mosley, 2014; Cull et al., 2009) while at the same time being a sustainable business model where customers generally repay their loans (Morduch, 1999).

To overcome screening and repayment problems, new loan products such as lending with joint liability and short-term step-wise loans (progressive lending) were introduced following the advent of the microfinance industry (Armendáriz & Morduch, 2010; Hulme & Mosley, 1996). These innovations improved repayment rates substantially. Today, the microfinance industry reports lower NPLs rates than many traditional banking markets (Rosenberg et al., 2009; Sievers & Vandenberg, 2007). The average repayment rate in microfinance is about 97% (Cull et al., 2009), which is indeed impressive considering that these are uncollateralized loans given to economically poor people operating businesses in informal markets in emerging economies.

However, in attempts to improve repayment rates, it seems that MFIs have relegated their cost efficiency to the background. This is because, while NPLs rates in microfinance are under control, operating costs remain high. As we mentioned in the Introduction, access to capital for micro-enterprises was a major focus of microfinance. Micro-enterprises at the bottom of the pyramid in the informal sector are normally profitable (Armendáriz & Morduch, 2010); hence, they are generally willing to pay high interest (Lucas, 1990). Due to the high demand for capital of micro-businesses, MFIs focused on lending at the expense of their cost efficiency;

after all, the cost of lending can be passed on to the borrower.

Thus, from an efficiency perspective, microfinance is a high-cost business (Gonzalez, 2007; Hardy et al., 2003). Mersland and Strøm (2009) report an operating cost to loan portfolio ratio of approximately 31%, which is 20 times higher than what is normal in the most efficient banking markets, like those in the Nordic countries (Berg, Førsund, Hjalmarsson, & Suominen, 1993). Of course, the high cost ratios in microfinance can partly be explained by the small loans (Helms & Reille, 2004) and the poor institutional frameworks where MFIs operate (Kirkpatrick & Maimbo, 2002). But, in addition, we argue that too much focus on risk could be another contributing factor. Therefore, we hypothesize that:

H1. There is a negative relationship between non-performing loans and cost inefficiency of microfinance institutions.

However, the theoretical arguments of Hughes and Mester (1993) and Berger and DeYoung (1997) as well as many empirical studies using mainstream banking data suggest that there is a positive relationship between operating costs and NPLs. In particular, using U.S. commercial banking data from 1985 to 1994, Berger and DeYoung (1997) find that when NPLs increase exogenously (due to external shocks), operating costs also increase. Their results also show that an increase in operating costs due to poor management practices eventually leads to higher NPLs. Similarly, Kwan and Eisenbeis (1997) find that inefficient banks are more prone to risk-taking compared to efficient banks. Berger and DeYoung (1997) further report that banks that skimp on selection costs in the name of cost efficiency end up having higher NPLs and higher operating costs in the long run. When a small amount of resources are allocated to the screening and selection of applicants, low-quality loans are made, which often surface in the future as NPLs. To control these, banks have to incur costs.

Applying the approach of Berger and DeYoung (1997) in the context of European commercial banking, Williams (2004) confirms that poorly managed banks make low-quality loans, which result in higher NPLs. He also finds an insignificant positive correlation between operating costs and NPLs with respect to the bad luck and skimping hypotheses of Berger and DeYoung (1997). In the same spirit, Fiordelisi et al. (2011) confirm the "bad management" hypothesis of Berger and DeYoung (1997). That is, inefficient European banks tend to have more problem loans. Similarly, using data from Malaysia and Singapore, Karim, Chan, and Hassan (2010) document findings that support those of Berger and DeYoung (1997).

As mentioned earlier, this positive relationship between operating costs and NPLs may also be expected in microfinance because of its banking logic (Armendáriz & Morduch, 2010; Battilana & Dorado, 2010). Specifically, external shocks such as floods, droughts, crop losses, and infectious diseases affecting the productivity of farmers in rural areas where the majority of the MFIs' clients live (Armendáriz & Morduch, 2010) could increase the NPLs of MFIs. Moreover, based on the skimping and bad management hypotheses of Berger and DeYoung (1997), some MFIs may be struggling with NPLs today due to a failure to conduct strict screening and monitoring in the past. Obviously, these are MFIs that do not practice relationship banking. Thus, extra efforts are needed today to control the increasing risk. Therefore, we formulate a rival hypothesis to H1 as follows.

H2. There is a positive relationship between non-performing loans and cost inefficiency of microfinance institutions.

Taken together, the negative (H1) and positive (H2) hypotheses do not rule out a nonlinear relationship between NPLs and cost inefficiency (i.e., operating costs) of MFIs. This is because MFIs vary in a wide range of dimensions, including management practice, geographical focus, lending method, and organizational form (Armendáriz & Morduch, 2010). Some MFIs may be efficient in controlling both operating costs and NPLs, other MFIs may be concerned with NPLs and hence practice relationship banking in order to enhance asset quality, which comes with high selection and monitoring costs, while still other MFIs may be poorly managed and hence incur high operating costs and high NPLs.

Geographically, MFIs serve different groups of clients. Some target only rural clients, others focus only on urban clients, while still others serve both urban and rural clients (Mersland & Strøm, 2009). This suggests that costs and NPLs may vary among MFIs with different geographical foci. For instance, the bad luck hypothesis of Berger and DeYoung (1997) may be more pronounced among MFIs with a purely rural focus.

Furthermore, based on the skimping hypothesis, it is possible that some MFIs may look efficient today in order to attract funding from investors and donors, but this strategy may have long-term consequences on asset quality and monitoring costs. Additionally, while some MFIs (e.g., the famous Grameen Bank in Bangladesh and BancoSol in Bolivia) focus on granting loans to groups, other MFIs practice only the individual-lending method (Armendáriz & Morduch, 2010). Group lending is generally believed to be correlated with lower costs and lower risk (Armendáriz & Morduch, 2010; Ghatak & Guinnane, 1999). This suggests that costs and NPLs may also differ between group-lending and individual-lending MFIs.

Finally, MFIs are incorporated as either shareholder-owned (banks and nonbank financial institutions) or non-profit organizations (e.g., non-governmental organizations) (Mersland, 2009). Owners have incentives to monitor the institution to ensure that excessive risks are not taken by management. Galema, Lensink, and Mersland (2012) find that excessive risk-taking is more likely in MFIs without owners than in shareholder MFIs. Overall, the above discussions imply different relationships between operating costs and NPLs among different MFIs. Thus, in the empirical analysis, it will not be surprising to find evidence supporting the two hypotheses (a nonlinear relationship). Thus, we propose a third hypothesis.

H3. The relationship between non-performing loans and cost inefficiency of microfinance institutions is nonlinear.

3 | DATA AND METHODOLOGY

3.1 | Data

Our dataset is an unbalanced panel of MFIs around the world. It is based on hand-collected rating reports from

TABLE 1 Distribution of number of microfinance institutions by country

#	Country	No. of MFIs	#	Country	No. of MFIs	#	Country	No. of MFIs
1	Albania	3	30	Mexico	31	59	Tajikistan	11
2	Argentina	2	31	Moldova	2	60	Croatia	1
3	Armenia	6	32	Morocco	8	61	Chad	3
4	Benin	8	33	Nicaragua	14	62	Rwanda	12
5	Bolivia	17	34	Pakistan	2	63	Zambia	3
6	Bosnia and Herzegovina	12	35	Paraguay	2	64	China	5
7	Brazil	14	36	Peru	40	65	Serbia	2
8	Bulgaria	3	37	Philippines	22	66	Ghana	5
9	Burkina Faso	9	38	Romania	7	67	Malawi	2
10	Cambodia	14	39	Russia	17	68	Gambia	1
11	Chile	2	40	Senegal	12	69	Kosovo	5
12	Colombia	14	41	South Africa	4	70	Congo	1
13	Dominican Republic	7	42	Sri Lanka	2	71	Burundi	6
14	Ecuador	20	43	Tanzania	8	72	Niger	8
15	Egypt	6	44	Togo	5	73	Dem. Rep. Congo	1
16	El Salvador	7	45	Trinidad and Tobago	1	74	Afghanistan	2
17	Ethiopia	10	46	Tunisia	1	75	Costa Rica	3
18	Georgia	8	47	Uganda	25	76	Lebanon	2
19	Guatemala	8	48	Montenegro	2	77	Turkey	1
20	Haiti	3	49	Cameroon	5	78	Palestine	3
21	Honduras	13	50	Guinea	3	79	Comoros	1
22	India	32	51	Timor	1	80	Italy	3
23	Indonesia	4	52	Bangladesh	2	81	Samoa	1
24	Jordan	3	53	Nepal	5	82	Sierra Leone	1
25	Kazakhstan	8	54	Vietnam	4	83	South Sudan	1
26	Kenya	18	55	Azerbaijan	9	84	United Kingdom	1
27	Kyrgyz Republic	9	56	Mongolia	4	85	Yemen	1
28	Madagascar	3	57	Nigeria	6	86	Angola	1
29	Mali	11	58	Mozambique	1	87	Macedonia	1
							Total	**607**

five leading microfinance rating agencies (MicroRate, Microfinanza, Planet Rating, Crisil, and M-Cril). These rating agencies were originally approved by the Rating Fund of the Consultative Group to Assist the Poor (C-GAP), a microfinance branch of the World Bank. The rating reports contain information concerning the MFI and its governance, management, financial profile, and operations. Thus, these reports in microfinance go beyond creditworthiness as in traditional credit rating to include trustworthiness and excellence (Tchuigoua, 2015).

The sample consists of 607 rated MFIs operating in 87 countries (see Table 1), observed over an unbalanced period of 18 years (1998–2015), with a common aim of operating professional and sustainable services and attracting funding from investors and donors. Former versions of the dataset have been used in high impact studies like Hartarska and Mersland (2012) and Mersland and Strøm (2009). Additionally, we use data from the World Bank to control for country effects. Table 2 provides a list of all variables used in this study.

Table 3 presents summary statistics of the variables used in the estimations. On average, operating costs amount to US$ 1.9 million, annual salary per employee is US$ 7,607, and the ratio of non-labor operating expenses to net fixed capital is 3.1. In terms of client base, the average MFI has 20,897 active clients, the majority of whom are borrowers (18,058). The average MFI is about 11 years old with approximately US$ 15 million total assets, majority of which are loan assets (US$ 11 million), and 6% portfolio at risk.

Interestingly, group lending is not the dominant uncollateralized lending method. About 42% of the MFIs offer group loans and the remaining majority (58%) give individual loans. In terms of ownership, about 37% of the MFIs are shareholder-owned while the remaining 63% are non-shareholder-owned (i.e., they are mutual organizations organized as member-based cooperatives or non-governmental organizations). Concerning their geographical focus, 27% of the MFIs focus on urban areas as their main market, 18% target only rural areas, and the rest of the MFIs serve both urban and rural clients. Finally, the mean for gross domestic product (GDP) per capita adjusted for purchasing power parity is US$ 6,533.

Table 4 presents pairwise correlations between the independent variables. Majority of them are significant at the 5% level or lower. All the correlations but the one between loan portfolio and total assets are below suggested thresholds of 0.80 (Studenmund, 2011) and 0.90 (Hair, Black, Babin, & Anderson, 2010). The high correlation between loan portfolio and total assets is expected since majority of the total assets are loan assets. Similarly, the high correlation between borrowers and clients is expected because borrowers form part of total clients. However, these high correlations should not be a concern because those variables are not used at the same time in an empirical model. Overall, the pairwise correlation matrix suggests that multicollinearity is not a significant problem in this study.

TABLE 2 Definitions of variables

Variable	Definition
Cost function	
Operating cost	This consists of personnel and non-personnel expenses.
Loan portfolio	Annual gross outstanding loan portfolio.
Number of clients	This consists of number active borrowers and savers.
Price of labour	Annual average salary per employee.
Physical capital	Calculated as non-labor expenses divided by net fixed assets.
Year	Year takes values from 1 to 11, and accounts for technological changes over time.
GDP per capita	Annual gross domestic product adjusted for purchasing power parity (constant 2011).
Inefficiency equation	
Portfolio at risk	30-day non-performing loans. That's, share of loan portfolio in arrears for more than 30 days.
MFI age (experience)	Number of years in operation as a microfinance institution.
MFI size	Total assets (log values used in estimations).
Group loans	1 = if loans are made mainly to groups, 0 = individuals.
Shareholder firm (SHF)	1 = shareholder owned firm (i.e., banks and non-financial financial institutions), 0 = non-shareholder-owned firm (i.e., non-governmental organizations and cooperatives).
Urban market	1 = if urban area is emphasized as main market, 0 = otherwise.
Rural market	1 = if rural area is emphasized as main market, 0 = otherwise.

3.2 | Methodology

Cost efficiency is measured in terms of how close an MFI's costs are to those of a best practice MFI, assuming both produce similar output under identical production settings (Fries & Taci, 2005; Hanousek, Shamshur, & Tresl, 2019; Hermes, Lensink, & Meesters, 2011). Technically efficient firms are those making maximum use of available inputs (i.e., technical efficiency = 1) (Hanousek et al., 2019). Cost efficiency concerns cost savings achieved when the MFI is efficient in terms of resource

TABLE 3 Descriptive statistics of variables

Variable	Mean	*SD*	Minimum	Maximum	Obs.
Operating cost (US$ 000)	1875.28	3,239.78	30.10	29,940.00	3,120
Number of clients	20,896.71	34,990.92	205.00	249,531.00	2,624
Number of borrowers	18,058.14	30,338.63	204.00	238,140.00	2,959
Wage per staff (US$)	7,607.00	6,510.01	152.46	84,317.66	2,754
Loan portfolio (US$ 000)	11,176.45	24,184.533	24.90	283,811.00	3,237
Physical capital	3.06	4.03	0.03	39.99	2,966
Year	9.20	3.29	1.00	18.00	3,296
GDP per capita (US$)	6,533.41	5,007.46	703.39	26,429.35	3,244
Portfolio at risk (PAR30) (%)	6.06	7.50	0.10	48.90	2,777
MFI age (years)	10.76	6.33	2.00	33.00	3,078
Total assets (US$ 000)	14,944.97	33,153.54	50.00	365,256.99	3,219
Shareholder MFI	0.37	0.48	0.00	1.00	3,049
Group lending	0.42	0.49	0.00	1.00	2,842
Urban market	0.26	0.44	0.00	1.00	2,641
Rural market	0.18	0.38	0.00	1.00	2,641

allocation and technical capabilities. Because cost functions cannot be observed directly, inefficiencies are normally compared to an efficient cost frontier (Hermes et al., 2011).

In general, cost efficiency is investigated by employing either data envelopment analysis (DEA) or stochastic frontier analysis (SFA). The latter technique is applied in this article because it takes into account both measurement errors and random effects (Hermes et al., 2011; Silva, Tabak, Cajueiro, & Dias, 2017). DEA on the other hand is not able to decompose the residual into the statistical noise and the inefficiency effect. Moreover, compared to DEA, SFA offers an opportunity to uniquely specify the empirical model in order to test a particular hypothesis (Hjalmarsson, Kumbhakar, & Heshmati, 1996). SFA has been used previously in other microfinance studies (e.g., Hartarska et al., 2013; Hartarska & Mersland, 2012; Hermes et al., 2011).

Specifically, this paper uses Battese and Coelli (1995) one-step SFA, which has been applied to MFIs by Hermes et al. (2011) and Safiullah and Shamsuddin (2019). One main advantage of the Battese and Coelli (BC) model over the traditional two-step SFA proposed by Aigner, Lovell, and Schmidt (1977) is that the BC model estimates both the cost frontier and the inefficiency equation at the same time. Moreover, Wang and Schmidt (2002) show that the two-step approach produces biased coefficients since it suffers from the assumption that the efficiency term is independent and identically truncated and normally distributed in the first step, while in the second step the efficiency terms are assumed to be normally distributed and dependent on the explanatory variables.

To specify the cost function, we follow the Sealey and Lindley (1977) model, which has been applied in microfinance studies, including Hermes et al. (2011) and Hartarska and Mersland (2012). The model views MFIs as financial intermediaries in channeling funds from depositors, lenders, and donors to borrowers. The translog cost function is specified in Equation (2), following Hermes et al.'s (2011) and Hartarska and Mersland's (2012) specifications, with a few modifications to suit this study's purpose. For instance, we do not include interest expense as in Hermes et al. (2011) or price of financial capital as in Hartarska and Mersland (2012) because we are concerned only with operating costs. The translog specification, which we apply, is the most applied model in cost-efficiency studies because of its flexibility in functional form[1] (Christensen, Jorgensen, & Lau, 1973; Greene, 1980; Karim et al., 2010).

$$
\begin{aligned}
\ln\left(OC_{itj}\right) = {} & \beta_0 + \beta_1 \ln\left(Clients_{itj}\right) + \beta_2 ln\left(Wage_{itj}\right) \\
& + \beta_3 \ln\left(Physical_{itj}\right) + \beta_4 ln\left(Clients^2_{itj}\right) + \beta_5 \ln\left(Wage^2_{itj}\right) \\
& + \beta_6 \ln\left(Physical^2_{itj}\right) + \beta_7\, ln\left(Wage_{itj}\right) x\, ln\left(Physical_{itj}\right) \\
& + \beta_8\, ln\left(Wage_{itj}\right) x\, ln\left(Clients_{itj}\right) + \beta_9\, ln\left(Physical_{itj}\right) \\
& x\, ln\left(Clients_{itj}\right) + \beta_{10} PAR30_{itj} + \beta_{11} Year_{tj} \\
& + \beta_{12} \ln\left(GDP_{tj}\right) + u_{itj} + v_{itj}
\end{aligned}
\tag{2}
$$

In Equation (2), *OC* is the total operating costs of MFI *i* at time *t* located in country *j*, *Wage* represents annual

TABLE 4 Pairwise correlations among independent variables

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Portfolio	1.000												
2. Clients	0.622*	1.000											
3. Borrowers	0.668*	0.949*	1.000										
4. Labour	0.488*	0.021	0.117*	1.000									
5. Physical	−0.117*	−0.116*	−0.067*	0.136*	1.000								
6. Year	0.358*	0.2079*	0.188*	0.193*	0.041	1.000							
7. GDP/cap	0.202*	−0.194*	−0.100*	0.438*	0.099*	0.055	1.000						
8. PAR30	−0.150*	−0.149*	−0.201*	−0.051	−0.047	−0.065	−0.100*	1.000					
9. Age	0.317*	0.253*	0.258*	0.096*	−0.138*	0.283*	0.047	0.080*	1.000				
10. SHF	0.146*	−0.002	0.080*	0.117*	0.141*	0.131*	−0.057	−0.043	−0.185*	1.000			
11. Group	−0.259*	0.177*	0.209*	−0.218*	0.161*	−0.036	−0.217*	−0.138*	−0.106*	−0.075*	1.000		
12. Urban	−0.042	−0.116*	−0.124*	0.125*	0.088*	−0.207*	0.101*	0.035	−0.094*	−0.011	−0.149*	1.000	
13. Rural	−0.148*	−0.027	−0.004	−0.199*	0.014	−0.071*	−0.118*	−0.027	−0.094*	0.036	0.180*	−0.285*	1.000
14. Size	0.965*	0.642*	0.673*	0.457*	−0.155*	0.333*	0.165*	−0.127*	0.318*	0.145*	−0.244*	−0.041	−0.127*

Note: The table reports pairwise correlations among explanatory variables. *Size* is the natural logarithm of total assets.

Abbreviations: GDP/cap, GDP per capita (log); SHF, shareholder firm.

*Denotes statistical significance at the 5% level or lower.

price per unit of labor, and *physical* represents physical capital, calculated as operating costs minus personnel costs divided by fixed assets (Hartarska & Mersland, 2012). C*lients* is an output measure representing the number of active clients (both borrowers and savers); alternatively, we use the number of borrowers as an output measure, following Hartarska and Mersland (2012). *ln* denotes natural logarithm. *PAR30*, *Year* and *GDP* are control variables. Portfolio at risk (*PAR30*), explained below, is included to control for the direct effect of credit risk on operating cost. *Year* ranges from 1 to 18 (representing 1998 to 2015) and it controls for changes in technology over time (Battese & Coelli, 1995) and GDP represents GDP per capita (Fries & Taci, 2005), adjusted for purchasing power parity, and it controls for country differences. u_{itj} is the inefficiency component, assumed to have a truncated-normal distribution that is independently but not identically distributed over different MFIs. v_{itj} is a random error term.

As the aim of the article is to investigate the relationship between NPLs and efficiency, we now turn to the main empirical model: the inefficiency Equation (3). In Equation (3), the inefficiency component (from the cost frontier) is the dependent variable and the indicator of NPLs is the independent variable. The model also includes MFI-level control variables, which may influence inefficiency. Thus, the mean inefficiency is modeled as a function of MFI-level covariates as follows.

$$U_{itj} = \delta_0 + \delta_1\left(PAR30_{itj}\right) + \delta_2\left(PAR30^2_{itj}\right) + \delta_3\left(Age_{itj}\right) + \delta_4\left(SHF_{itj}\right) + \delta_5\left(Group_{itj}\right) + \delta_6\left(Urban_{itj}\right) + \delta_7\left(Rural_{itj}\right) + \delta_8 ln\left(Size_{itj}\right) + \varepsilon_{itj} \tag{3}$$

In Equation (3), U_{itj} is the inefficiency distribution of the i^{th} MFI at time t in country j. It represents the first moment condition, where more of it means a high likelihood that the MFI is inefficient. *PAR30* is the portfolio at risk (over 30 days). NPLs rate is the most common measure of credit risk in banking and it is defined as the proportion of the loan portfolio that is more than 90 days overdue (Kwan & Eisenbeis, 1997). In the microfinance industry, a shorter period (30 days) is often used since loans are mostly short-term in nature and, as a result, NPLs are commonly referred to as portfolio at risk more than 30 days overdue (*PAR30*). Thus, in this article, we use *PAR30* and NPLs interchangeably.

PAR30 has been used in other studies such as Caudill et al. (2009), Mersland and Strøm (2009), and Kar (2012). A higher loan portfolio quality signifies a smaller portfolio at risk. Since the dependent variable represents inefficiency, the negative coefficient of this variable means that an MFI becomes efficient as NPLs increase.

Following Hermes et al. (2011), we include MFI *age* and lending method (*group loans*). In addition, we control for MFIs' ownership structure (*shareholder-owned firms*) (Fries & Taci, 2005), geographical markets (*only urban* and *only rural*), and *size*. Thus, heteroscedasticity in the variance of the inefficiency is explained not only by NPLs but also by other covariates It has been suggested that it is costly to offer individual loans, compared to group loans (Ghatak & Guinnane, 1999); thus technical inefficiency may vary between providers of group and individual loans. With respect to MFI age (or experience), learning curve theory suggests that MFIs' efficiency improves over time (Caudill et al., 2009), which implies fewer technical inefficiencies over time. In the empirical analysis, non-shareholder-owned MFIs (mutual ownership), individual-lending MFIs, and MFIs that serve both urban and rural clients are the reference categories for ownership, lending method, and geographical market, respectively.

MFI size is measured as the natural logarithm of total assets. Economies of scale are usually correlated with size, as Hartarska et al. (2013) have confirmed in microfinance. This suggests that the variance in the inefficiency component could be heteroscedastic due to size effects.

As a robustness check, we employ Greene's (2005) true fixed-effects SFA model, in addition to the random-effects BC model,[2] to control for heterogeneity across MFIs. The fixed-effects model allows for a separation of time-varying inefficiency from MFI-specific time-invariant unobserved effects. Finally, to control for possible endogeneity bias between NPLs and operating costs, we run the Granger-causality test (Berger & DeYoung, 1997). Granger-causality test is normally used to determine whether one variable "Granger-cause" another (Granger, 1969). The test results (see next section) show that operating costs do not Granger-cause NPLs, rather, NPLs Granger-cause operating costs. Despite the Granger-causality test results, we employ a dynamic panel modelling technique, specifically Blundell and Bond's (1998) system GMM model, to further ensure that our estimates are not influenced by possible endogeneity bias.

The GMM (generalized method of moments) model uses "internal" instruments to solve endogeneity. Reliable estimates of this model require that the null hypotheses of both the second-order autocorrelation and Hansen J tests are not rejected (Arellano & Bond, 1991). The second-order serial correlation test is under the null hypothesis that there is no second-order autocorrelation in the residuals from differenced equations while the

TABLE 5 The cost function, and the link between NPLs and inefficiency of MFIs

	(1)	(2)	(3)
Panel A: Cost frontier equation			
Y (output is the number of clients)	−0.8192***	0.0494	
	(0.2109)	(0.1447)	
Y (output is the number of borrowers)			0.2731**
			(0.1346)
Y ˆ2	0.0339***	0.0152***	0.0315***
	(0.0071)	(0.0055)	(0.0053)
Price of labor	−0.8110**	0.0717	0.9201***
	(0.3402)	(0.3009)	(0.2625)
Price of labor ˆ2	0.0371**	0.0068	−0.0039
	(0.0166)	(0.0162)	(0.0145)
Physical capital	−0.2522	−0.2328	0.5660***
	(0.1954)	(0.1763)	(0.1405)
Physical capital ˆ2	−0.0322***	0.0188**	0.0122*
	(0.0096)	(0.0077)	(0.0070)
Price of labor * Physical capital	0.0261	−0.0026	−0.0583***
	(0.0184)	(0.0179)	(0.0150)
Y* Price of labor	0.0997***	0.0108	−0.0347**
	(0.0176)	(0.0160)	(0.0152)
Y* Physical capital	0.0136	0.0344***	0.0032
	(0.0113)	(0.0098)	(0.0092)
Portfolio at risk (PAR30)	0.0000	0.0076***	0.0071***
	(0.0021)	(0.0015)	(0.0014)
Year	0.0195***	0.1483***	0.0964***
	(0.0048)	(0.0060)	(0.0053)
GDP per capita	0.1508***	−0.0882	0.4586***
	(0.0225)	(0.0995)	(0.0943)
Constant	−2.1291	9.7371	9.8814
	(2.0785)	(1.0250)	(3.0180)

	(1)	(2)	(3)
Panel B: Inefficiency equation			
Portfolio at risk (PAR30)	−0.0669***	−0.2202**	−0.1892**
	(0.0220)	(0.0912)	(0.1136)
Portfolio at risk ˆ2	0.0016***	0.0062***	0.0054***
	(0.0006)	(0.0023)	(0.0028)
MFI age	0.0963***	0.0625	0.0338
	(0.0129)	(0.0384)	(0.0356)
Shareholder MFI	0.3104**	−0.5398	−0.9818
	(0.1487)	(24.3242)	(32.5952)
Group loans	−0.2427	−0.3095	−0.3315***
	(0.1499)	(0.3090)	(0.4247)
Urban market	−0.0453	−1.1997**	−1.7615***
	(0.1357)	(0.5962)	(1.5529)

(Continues)

TABLE 5 (Continued)

	(1)	(2)	(3)
Rural market	0.0548	−2.5680	−5.5743
	(0.1647)	(3.9695)	(0.03040)
MFI size	0.8868***	−0.0954	−0.1492
	(0.0901)	(0.1457)	(0.1891)
Constant	−15.7948***	−2.2312	−0.7260
	(1.5067)	(2.3982)	(3.1385)
Observations	1,577	1,483	1,595
Number of MFIs	400	306	330
Wald chi-square	3,459.63***	9,618.60***	11,925.84***
Log likelihood	−1,085.78	182.97	289.61
Estimation method	Random effects	True fixed effects	True fixed effects

Note: This table reports panel stochastic frontier analysis estimates of Battese and Coelli's (1995) random-effects time-varying inefficiency-effects model (1) and Greene's (2005) true fixed-effects model (models (2) and (3)). In Panel A (the cost function), O*perating costs* is the dependent variable and output is measured in terms of number of active clients (borrowers and savers) and number of active borrowers (for simplicity, Y is used to denote output measure, especially when interacting it with input price). The inputs are *Price of labor*–annual salary per employee, and *Physical capital*, measured as non-labor expenses divided by net fixed assets. Control variables are *Year*, a categorical variable, which runs from 1 to 11, and accounts for technological changes over time, and *GDP* per capita, the annual gross domestic product adjusted for purchasing power parity (constant 2011). Standard errors are in parentheses. In Panel B (inefficiency equation), inefficiency is the dependent variable, generated simultaneously from the cost frontier (Panel A). *Portfolio at risk (PaR30)* is the proportion of loan portfolio that is in arrears over 30 days, *MFI age* is the number of years the institution has been operating as a microfinance organization, *Shareholder MFI* = 1 if shareholder-owned firm and = 0 if non-shareholder-owned firm, *Group* = 1 if solidarity group loans and = 0 if individual loans, *Urban* market = 1 if urban market is emphasized and = 0 if otherwise, *Rural market* = 1 if rural market is emphasized and = 0 if otherwise and, finally, *MFI size* is measured in terms of total assets. Standard errors are in parentheses.
*Denotes statistical significance at the 10% level.
**Denotes statistical significance at the 5% level.
***Denotes statistical significance at the 1% level.

Hansen test is under the null hypothesis that the set of instruments used is valid. In this study, the two null hypotheses are not rejected, which suggest that our GMM estimates are reliable.

4 | RESULTS AND DISCUSSIONS

Table 5 reports the results of the cost function (Panel A) and those relating to the inefficiency equation (Panel B). Model (1) contains the estimates of Battese and Coelli's (1995) model, while models (2) and (3) report those based on Greene's (2005) model. In both methods, we assume the inefficiency term has a truncated-normal distribution.

If a variable has a positive coefficient in Panel A (of Table 5), it means an outward departure from the cost frontier—suggesting higher costs. In general, the true fixed-effects estimates are similar to those based on the random-effects estimator with few exceptions. Both output measures and their quadratic terms are significant. Number of clients has negative and positive coefficients on its linear and quadratic terms, respectively (see model 1). This suggests that there is an optimal level of number of clients below which operating costs are lower and beyond which the costs are higher. Number of borrowers on the other hand has a positive linear relationship with operating costs (in model 3, both the linear and quadratic terms of number of borrowers have positive coefficients). This suggests that serving a larger number of borrowers increases the operating costs of MFIs. This is not surprising since numerous transactions (e.g., average loan and savings) relating to borrowers and depositors are normally smaller in volume and each small transaction costs similarly to a big one. Model (1) also suggests that there is an optimal point of labor below which operating costs reduce and above which the costs increase. The results on *Physical capital* and its quadratic term seem to suggest a positive relationship between physical capital and costs.

In model (3), the interaction between labor and physical capital is negatively related to cost. However, the interaction between price of labor and number of total clients is positively related to cost (1) suggesting departure from cost frontier while the interaction between price of labor and number of borrowers is negatively related to cost (3). The interactions between each output measure (number of clients and borrowers) and physical capital have positive correlations with cost in all models,

TABLE 6 Nonperforming loans and inefficiency of MFIs: Vector autoregression

	Portfolio at risk (PAR30)	Inefficiency
Portfolio at risk (− 1)	1.2137	6.0381*
	(0.7910)	(3.1368)
Portfolio at risk (− 2)	−0.5048	−2.3086
	(0.8383)	(3.3247)
Portfolio at risk (− 3)	0.4760	5.4421*
	(0.7452)	(2.9553)
Portfolio at risk (− 4)	0.0200	−6.3846***
	(0.5168)	(2.0496)
Portfolio at risk (− 5)	−0.2979	−2.3596**
	(0.3030)	(1.2016)
Inefficiency (− 1)	−0.0573	−0.8934
	(0.1652)	(0.6551)
Inefficiency (− 2)	−0.1821	−0.1621
	(0.1242)	(0.4926)
Inefficiency (− 3)	0.1443	0.0440
	(0.1462)	(0.5798)
Inefficiency (− 4)	−0.2492*	−0.3983
	(0.1436)	(0.5694)
Inefficiency (− 5)	0.0795	1.6584***
	(0.1561)	(0.6190)
Constant	0.8437	2.3914
	(0.6830)	(2.7085)
R-squared	0.8867	0.9098
Observations(number of years)	13	13

Note: This table lists vector autoregression results (based on annual means). The inefficiency is obtained from the cost function when loan portfolio is used as output. Lag-order selection statistics (untabulated) show that 5 lags are appropriate. Standard errors in parentheses.
*Denotes statistical significance at the 10% level.
**Denotes statistical significance at the 5% level.
***Denotes statistical significance at the 1% level.

suggesting a departure from the cost frontier (however, only model 2 is significant). *Portfolio at risk (PAR30)* has a positive effect on operating cost (significant in two of the three models). However, the magnitude of its coefficients is small in all the three models. Thus, it seems that its impact lies more in the inefficiency equation. *Year* has positive effects on cost, suggesting that operational costs in MFIs are "sticky". One explanation is that technological changes over time are costly for MFIs to implement. Indeed, Hermes et al. (2011) find a positive long-term effect of technological changes on MFIs' cost. Finally, GDP per capita relates positively to operating costs, indicating that MFIs operating in more developed economies have higher operating costs. This finding is consistent with that of Grigorian and Manole (2002).

TABLE 7 Granger-causality test

Equation	Excluded	Chi2	Df	*P*-value
Portfolio at risk	Inefficiency	4.6148	5	.465
	ALL	4.6148	5	.465
Inefficiency	Portfolio at risk	13.923	5	.016
	ALL	13.923	5	.016

Note: Inefficiency is generated from the cost function when the output variable is loan portfolio.
Abbreviation: Df, degree of freedom.

Panel B (of Table 5) contains estimates of the inefficiency equation, the most important part of the empirical investigation. In this panel, the dependent variable is the inefficiency term (obtained simultaneously from the cost frontier; Panel A). The results show in all models that, indeed, there is a significant relationship between NPLs and cost inefficiency in microfinance. The significant negative effect of portfolio at risk (*PAR30*) on cost inefficiency indicates that an increase in NPLs reduces the inefficiency (or improves the efficiency) of MFIs. The finding implies that MFIs with low NPLs and high (cost) inefficiencies may benefit from relaxing extra monitoring efforts. This finding supports those of Altunbas et al. (2007), our claimed trade-off proposition and the relationship banking theory; hence, hypothesis 1 is supported.

The significant positive effect of the quadratic term[3] of *PAR30* on inefficiency shows that a further rise in NPLs increases the inefficiency of MFIs. To put it differently, as asset quality declines, so does the cost efficiency of MFIs. The finding implies that MFIs with high NPLs rates exert extra efforts to control NPLs. However, the extra efforts, like monitoring and negotiation of possible repayment plans, cause the overall operating costs of the institution to shoot up (Berger & DeYoung, 1997); hence, inefficiency increases (or efficiency deteriorates). This finding supports hypothesis 2.

The significant coefficients of both PAR30 (NPLs) and its quadratic term lend support for hypothesis 3, that the relationship between NPLs and inefficiency of MFIs is nonlinear[4] (U-shaped). The nonlinear curve means that there is an optimal point of *PAR30* above which cost inefficiency increases. We could not pin down that point because there seems to be no general optimal point of *PAR30* fitting all types of MFIs. While the majority of MFIs have *PAR30* below 10% of the portfolio value, there are some that have *PAR30* ranging from 10 to 50%. Therefore, we leave this threshold for practitioners to assess for themselves.

TABLE 8 Nonperforming loans and inefficiency of MFIs: System GMM

Dependent variable: inefficiency	(4)	(5)	(6)
Output variable in cost function	Loan portfolio	Number of clients	Number of borrowers
Inefficiency(t–1)	0.4435***	0.4097***	0.4194***
	(0.0378)	(0.0197)	(0.0201)
Portfolio at risk (PAR30)	−4.2581***	−0.0096	−0.6363*
	(1.5586)	(0.3445)	(0.3255)
Portfolio at risk ˆ2	13.6257***	0.8193	3.3463***
	(5.1705)	(1.2311)	(1.2390)
MFI age	0.0029	−0.0017***	−0.0011**
	(0.0019)	(0.0005)	(0.0005)
Shareholder MFI	0.0140	−0.0019	0.0004
	(0.0158)	(0.0065)	(0.0062)
Group loans	−0.0072	0.0011	−0.0048
	(0.0175)	(0.0063)	(0.0068)
Urban market	0.0164	−0.0189***	−0.0103*
	(0.0148)	(0.0065)	(0.0063)
Rural market	−0.0117	−0.0141*	−0.0082
	(0.0232)	(0.0084)	(0.0091)
MFI size	−0.0145	0.0037	0.0031
	(0.0091)	(0.0028)	(0.0028)
Constant	2.0855***	6.1910***	6.1366***
	(0.2006)	(0.2414)	(0.2446)
Observations	1,407	1,249	1,352
Number of MFIs	417	373	406
Number of instruments	36	36	36
AR(1) test (p-value)	0.014	0.049	0.029
AR(2) test (p-value)	0.256	0.163	0.190
Hansen test (p-value)	0.752	0.459	0.656
Chi2 test (p-value)	0.000	0.000	0.000

Note: This table reports results of system GMM. The dependent variable is inefficiency, which is obtained from the cost frontier estimation. AR (1) and AR (2) are tests for first- and second-order serial correlation in the first-differenced residuals, under the null hypothesis of no serial correlation. The Hansen test of over-identification is under the null hypothesis that the instrument set is valid. In specifying the GMM model, we use forward orthogonal deviations (because it is suitable for unbalanced panel [Roodman, 2009]), and the “collapse” option of limiting instrument proliferation. Standard errors are in parentheses.
*Denotes statistical significance at the 10% level.
**Denotes statistical significance at the 5% level.
***Denotes statistical significance at the 1% level.

Concerning the control variables in Panel B, we observe, in model (1), that older MFIs are cost inefficient compared to younger MFIs, similar to Hermes et al.'s (2011) finding. Perhaps younger MFIs are more able to keep abreast of current efficiency and technology practices compared to older MFIs, which may have to learn them by trial and error. A possible explanation is that the lack of learning effects among MFIs is a result of subsidies (Caudill et al., 2009). For example, about 70% of the MFIs in our sample hold subsidized debt. In any case, “sticky” operating costs are a major challenge in the industry and future research should definitely investigate why there are no cost-learning effects among MFIs globally.

Similarly, in model (1), shareholder-owned MFIs are more cost inefficient compared to non-shareholder-owned MFIs and this departs from the transformation debate that shareholder-owned firms are more operationally efficient than non-shareholder-owned firms (D'Espallier, Goedecke, Hudon, & Mersland, 2017). In untabulated regressions, we checked whether shareholder MFIs are indeed inefficient compared to nonshareholder MFIs by replacing the *Shareholder MFI* variable with *Bank*, *Nonbank and NGO* as controls for MFI type (co-operative is the base category). The results showed that nonbank and NGO MFIs are significantly and positively associated with higher cost inefficiencies compared to co-operative MFIs. The overall impression in our sample is that shareholder-owned MFIs are probably not different from non-shareholder MFIs in terms of cost efficiency. This suggests that both groups of MFIs probably apply similar business models.

We further observe that, as expected, group lending reduces MFIs' inefficiency compared to individual lending (significant only in model 3) (Ghatak & Guinnane, 1999) and MFIs focusing only on urban clients are more efficient compared to those serving both urban and rural clients (significant in models 2 and 3). Finally, and similarly to Hartarska and Mersland (2012), we find that MFI size increases cost inefficiency (model (1)), suggesting diseconomies of scale.

To check whether it is really NPLs that cause operating costs, we run vector autoregressive (VAR) model and the Granger-causality test. As shown in Table 6, previous values (four lags) of NPLs (PAR30) are significantly related to the operating costs (inefficiency) of MFIs; the lags of inefficiency in the PAR30 equation are generally insignificant (only one lag is significant at 10% level). Interestingly, the nonlinear relationship is also reflected in the VAR results as $PAR30_{t-3}$ to $PAR30_{t-5}$ are negatively and significantly related to inefficiency while $PAR30_{t-1}$ is positively related to inefficiency. Again, the (past) negative association confirms our trade-off argument as well as the relationship banking theory regarding NPLs and operating costs. Overall, increase in NPLs will initially reduce the inefficiency (operating costs) and further increase will worsen inefficiency (operating costs), hence, the nonlinear (U-curve) relationship. Again, this supports hypothesis 3.

Table 7 shows the Granger-causality test results, which indicate that the joint effect of all the five lags of PAR30 on inefficiency is statistically significant at the traditional 5% level while that of the inefficiency is insignificant (thus, the null hypothesis that operating costs do not "Granger-cause" NPLs cannot be rejected). Thus, the Granger-causality test suggests that it is the NPLs that influence the operating costs of MFIs, and not the operating costs driving NPLs.

As a final robustness check, we use system GMM model to test the relationship between NPLs and cost inefficiency. The aim of this approach is to further address possible reversed causality problem (Berger & DeYoung, 1997) even though the Granger-causality test (Table 7) does not show evidence of its presence in this study. To do this, we run three cost frontier models using loan portfolio, number of total clients, and number of borrowers as output variables respectively, and obtain the inefficiency scores. The inefficiency scores are then used as dependent variables in the system GMM model. The results (Table 8) confirm the nonlinear (U-shaped) relationship between the NPLs and inefficiency of MFIs. Again, both PAR30 and its quadratic term statistically significant in two of the three models. Moreover, the coefficients' signs of portfolio at risk and its quadratic term are the same as those in Table 5 and this makes our findings robust.

Overall, we find a nonlinear relationship between NPLs and cost inefficiency in microfinance, contrary to the linear relationship reported in traditional banking studies (e.g., Altunbas et al., 2007; Berger & DeYoung, 1997; Fiordelisi et al., 2011; Williams, 2004). The U-shaped relationship indicates that, at some point, an increase in NPLs reduces inefficiency (or improves cost efficiency) but a further increase (beyond that point) increases the inefficiency of MFIs.

5 | CONCLUSIONS

In this article, we examine the relationship between nonperforming loans (NPLs) and cost efficiency of microfinance institutions (MFIs). While there is a significant body of banking literature on the aforesaid relationship (e.g., Berger & DeYoung, 1997; Fiordelisi et al., 2011; Williams, 2004), studies using microfinance data are, to the best of our knowledge, nonexistent. This is unfortunate since high operating costs are hampering the microfinance industry and these could be related to historical reasons where MFIs were too concerned about repayment performance and not concerned enough about operational costs. As a solution to high NPLs rates among government banks tasked with agricultural lending, modern microfinance emerged in the 1970s (Hulme & Mosley, 1996), and it remains a successful banking market for the poor today (Armendáriz & Morduch, 2010). Microfinance pioneers shifted the lending focus to nonfarm businesses, which are less vulnerable to weather shocks, and this strategy resulted in massive improvements in repayment rates (Cull et al., 2009).

However, focusing on access to capital and not on the price of capital has resulted in huge operating costs in the global microfinance industry today. MFIs paid little attention to their cost efficiency because the cost of lending can always be passed on to borrowers, who are normally profitable and willing to pay high interest (Armendáriz & Morduch, 2010). We therefore study a possible trade-off between (low) NPLs and (high) operating costs in the global microfinance industry. After all, modern microfinance has been successful in achieving high loan asset quality (Cull et al., 2009; Hulme & Mosley, 1996), but not cost efficiency.

Our motivation in investigating the claimed trade-off is linked to the high lending rates in the microfinance industry. The high operating costs force MFIs to increase their interest rates (Battilana & Dorado, 2010; Hardy et al., 2003), which harms the good reputation of microfinance (Bateman, 2010). Thus, reducing operating costs could mean reducing interest rates, which could bring some relief to the poor borrower. Moreover, an overemphasis on repayment performance may render MFIs unwilling to serve some of their target clientele–the most vulnerable ones (Amin et al., 2003; Pearlman, 2012).

Using a large global sample of MFIs, we find that the relationship between NPLs and inefficiency is nonlinear (U-shaped), contrary to the evidence for a positive linear relationship reported in commercial banking studies. In particular, we find that an initial increase in NPLs reduces inefficiency while a subsequent increase worsens it. Our finding is consistent with two streams of research. The first is relationship banking, which suggests that creating and maintaining ties with clients is costly (Diamond, 1984; Petersen & Rajan, 1994) but that it enhances asset quality (Puri et al., 2017). The second stream relates to the theoretical arguments of Hughes and Mester (1993) and Berger and DeYoung (1997) that efficiency and NPLs are positively related. For instance, exogenous events cause NPLs, which warrant extra monitoring costs. On the other hand, poorly managed institutions end up having a large stock of NPLs.

Our finding is relevant to practice. Each MFI needs to strike a reasonable balance between its cost efficiency and risk. MFIs operating with too low credit risk could find it operationally useful to streamline their selection, monitoring, and collection activities or increase risk a bit by relaxing efforts devoted to these activities. This would allow them to serve more vulnerable clients, thereby enhancing their social outreach and at the same time remaining operationally sustainable. On the other hand, MFIs struggling with high NPLs could benefit from installing more strict screening, monitoring, and collection procedures. The challenge however is how to do strict client selection without screening out the poorest clients. This calls for a selection model that maximizes both institutional and client benefits. This is an avenue for future research.

It would also be interesting to rigorously investigate why learning effects are lacking among MFIs around the world. Is it that younger MFIs have up-to-date owners and the older ones are dependent on donors? Another important avenue for future research is an investigation into the cost drivers of an MFI. To date, there has been limited research on the cost structure of a typical microfinance institution. What is the most important driver of operating costs in microfinance and how can digitalization help reduce such costs are questions that need to be addressed.

CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

ENDNOTES

[1] To determine the suitability of our translog model, we have performed three different tests (Likelihood-ratio test, Wald test, and Hausman test) and all tests results are significant at the 1% level, suggesting that the translog specification is preferred in this study. In both the Likelihood-ratio and the Hausman tests we compared the translog function with the Cobb–Douglas function while the Wald test is about parameter restrictions.

[2] Berger and DeYoung (1997) find that operating costs and NPLs are simultaneously determined (i.e., there is a reversed causality between the two). However, the use of the one-step SFA approach in this study makes this endogeneity bias less problematic since costs and NPLs enter separate models.

[3] The coefficients of the quadratic term of PAR30 are lower than those of the linear term. This means that the net effect of PAR30 on cost inefficiency is negative and suggests that MFIs could relax/streamline their monitoring efforts to improve cost efficiency. This relates to the main motivation of this study that the microfinance industry has, for too long, excessively focused on credit risk control at the expense of cost efficiency.

[4] In unreported robustness checks, we confirmed the nonlinear (U-shaped) relationship between cost inefficiency and NPLs in simple pooled OLS and fixed effects regressions. Also, the U-shaped relationship exists when loan portfolio is used as an output measure in the stochastic frontier analysis. We chose number of clients to reflect the double bottom line of MFIs.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request

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