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Efficiency and financial risk management practices of microfinance institutions

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Abstract

Microfinance institutions (MFIs) have evolved in different and complex ways to solve various market frictions, with some of them providing a wide range of financial products and using different lending technologies to reach poor and underserved populations. As a result, some MFIs are more efficient than others, but are efficiency gains aligned with risk management practices? The specific characteristics of the microfinance industry make the answer to this question less obvious than that of commercial banks. This paper tries to shed light on these issues by analysing the efficiency and risk management of MFIs and describing the potential implications of these relationships for the microfinance industry. After considering several measures of financial risk management ratios commonly used in the microfinance literature, our results show that cost efficiency improves asset quality and solvency of MFIs, but also reduces the need for holding idle cash or liquid assets. The results of this paper can help academics, policymakers, and regulators to better understand the impact of cost efficiency on financial risks management practices in the microfinance industry.

KEYWORDS

efficiency, financial risk, asset quality, capital ratio, liquidity management, microfinance institutions

1 | INTRODUCTION

Microfinance institutions (MFIs, hereafter) play a vital role in developing a more inclusive financial sector by providing access to finance to poor people and microenterprises not covered by the traditional banking sector (Ledgerwood et al., 2013). The unique business model of MFIs is characterized by having a twofold bottom-line: achieving simultaneously profitability (financial self-sufficiency) and poverty outreach (social mission). This business model requires the use of special lending technologies adapted to clients with lack of collateral, assets, and financial information (Armendáriz & Morduch, 2010), which include joint liability schemes and intensive screening and monitoring practices to achieve adequate levels of risk and returns. MFIs have evolved over time, reflecting the changes in the market and the need to achieve higher levels of financial inclusion in several countries (D'Espallier et al., 2017). Although not-for-profit MFIs were initially the predominant form of MFIs (e.g., NGOs and nonbank financial institutions); for-profit MFIs operating as banks (member-based) credit unions, and rural banks are becoming increasingly important and a part of the financial sector (Brown et al., 2016; Mersland & Strøm, 2009).

Mainstream literature on microfinance has been closely related to financial performance and outreach (Cull & Morduch, 2007; Mersland & Strøm, 2009, 2010) and the contribution of access to finance to poverty reduction (Bruhn & Love, 2014). However, given that MFIs have become more vulnerable to financial turmoil (Wagner & Winkler, 2013), MFI risk management practices have become an important topic to ensure financial stability. Previous research on MFI risk management practices has focused on operational or strategic risk and relied on qualitative data (e.g., interviews) to assess the risk of either their clients (Froelich et al., 2015) or their own management (Ibrahim, 2017; Kimathi et al., 2015); along with reports on the risks faced by MFIs (Ashta & Khan, 2012; Chetty, 2016; Fernando, 2007; GTZ, 2000; Mabhena, 2020; NBE, 2010; Oluyombo & Olabisi, 2008).

Against this background, using panel data econometric techniques, we analyse the underlying factors affecting the financial risk management practices of MFIs; paying special attention to the role of cost efficiency as a potential tool which can be used by MFIs to adjust their risk profile. This is particularly relevant for MFIs, as stricter risk management practices could result in lower levels of access to financial services for the most vulnerable population (Pearlman, 2012).

The aim of this paper is twofold. First, it provides new evidence in terms of the relationship between cost efficiency and three core areas of MFI financial risk management: credit risk, liquidity risk, and capital. The impact of efficiency on MFI risk management practices has received very little attention, contrary to banking organizations, where this has been widely studied (Berger & DeYoung, 1997; Fiordelisi et al., 2011; Hughes & Mester, 1998). To the best of our knowledge, this paper is the first to discuss the relationships between cost efficiency and risk management practices in the context of MFIs. This paper also considers the role of deposit-mobilization and profit orientation of MFIs, as potential factors influencing the link between cost efficiency and risk. Accepting deposits requires approval from regulatory authorities, and therefore not all MFIs qualify for this. Given that deposit-taking MFIs are able to fund loans using deposits from their customers, risk management practices are likely to be affected. In a similar way, for-profit and non-profit MFIs might exhibit a differential effect on risk management practices as they aim to maximize either profits or social objectives, respectively.

The use of stochastic frontier approach (SFA) and data envelopment analysis (DEA) to analyse efficiency in the context of microfinance institutions is relatively new, with some studies exploring the role of efficiency and governance, and mission drift (Caudill et al., 2009; Hartarska & Mersland, 2012; Hermes et al., 2011). Other efficiency-related work estimates scope economies derived from the joint provision of microloans (Hartarska et al., 2011, 2013).[1] Zamore et al. (2021) study for the first time the relationship between non-performing loans (NPLs) and cost efficiency using a worldwide sample of MFIs. Interestingly, the authors demonstrate the existence of a U-shaped relationship between inefficiency and NPLs rates in contrast to previous banking studies; suggesting that MFIs need to avoid an overemphasis on asset quality at the expense of cost efficiency. However, Zamore et al. (2021) focus on one specific aspect of financial risk management, that is, credit risk, while we provide a thorough assessment of a wide range of financial risk management indicators related to asset quality, solvency, capitalization, and liquidity risk. We use a cost function to capture efficiency and apply an approach employed in efficiency analyses of banks and financial institutions which also fits well with MFI sustainability goals (i.e., cost minimization and their goal of serving as many poor clients as possible rather than profit maximization), in line with previous studies (Hartarska et al., 2011). Given that operating costs in the microfinance industry are generally high, due to the extensive screening and monitoring process; the microfinance industry constitutes an interesting research setting to study the implications of cost efficiency on risk management practices in the context of MFIs.

Based on a sample of MFIs operating worldwide, our results, using panel data econometric techniques, show a negative (positive) effect between cost efficiency and credit risk (portfolio quality) in the microfinance industry. Our findings also suggest a negative effect between cost efficiency and liquidity position (measured by liquid assets/total assets and deposit/loan ratio). Finally, yet importantly, our findings show that cost efficiency is positively related to the capital position of MFIs. These findings are robust after implementing propensity score matching (PSM) techniques, suggesting that the treatment effects observed are not driven by underlying selection bias but rather reflect causal relationships.

Our contribution to the literature is twofold. First, although previous research has assessed the impact of cost efficiency on risk within the commercial banking sector, to date no research has analysed how cost efficiency affects several indicators of financial risk management in the context of microfinance institutions. More precisely, we follow the standard risk classification for MFIs around three core areas: asset quality or credit risk, solvency, liquidity management, as in previous literature

(Ledgerwood et al., 2013) to assess the potential effect of cost efficiency on MFI's financial risk management. To the best of our knowledge, no previous studies have explored the effects of cost efficiency on risk management practices for MFIs, with the exception of Zamore et al. (2021), who analyse the relationship between cost efficiency and non-performing loans (NPLs) only. In contrast to Zamore et al. (2021), who focused solely on credit risk, we conducted a comprehensive evaluation of financial risk management for MFIs. Our analysis covers a broad spectrum of indicators, including asset quality, solvency, and liquidity. By studying these relationships, this study also presents new evidence that could be helpful to understand the effects of the covid-19 pandemic on the management of financial risk of MFIs. MFIs have been likely to be negatively affected by Covid-19 due to an increase in vulnerable clients (households) who cannot meet their debt obligations (credit risk), but also pressures to meet their obligations (liquidity risk) and remain solvent (capital risk).

Second, we analyse the link between efficiency and risk by considering the differential effects related to the contribution of MFIs to mobilize deposits and the importance of maximizing social rather than financial objectives. We follow previous literature and classify MFIs as 'deposit-mobilizing' if they collect deposits (Hartarska et al., 2013). Although we do not have information on whether lending or savings are exclusively provided to their members or poor households, a common characteristic of MFIs is that they are typically specialized in providing financial services to the poor (Ledgerwood et al., 2013) and therefore a segment of the population that has been traditionally excluded from access to mainstream financial services. Therefore, this paper provides a comparison between these two relevant groups of MFIs, which are likely to have different approaches in terms of their financial risk management practices.

The remainder of the paper is organized as follows: Section 2 reviews the literature on efficiency and risk for MFIs; Section 3 explains the econometric methodology and discusses the data. Results are presented in Section 4 while Section 5 concludes and draws policy implications.

2 | LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Managing risk is a complex and increasingly important task for any financial organization in a world where economic events and financial systems are linked. Like all financial institutions, MFIs face risks that must manage efficiently and effectively to be successful. Those MFIs that manage risk effectively are less likely to be surprised by unexpected losses and more likely to build market credibility and capitalize on new opportunities. On the contrary, if the MFI does not manage its risks well, it will probably fail to meet its social and financial objectives. Inadequately managed risks are also likely to result in financial losses and a loss of confidence by lender, investors, and savers with a subsequent impact on the availability of funds. Consequently, MFIs with limited funds could find it increasingly difficult to meet their social goal of providing services to the poor and vulnerable population (GTZ, 2000). As MFIs develop and grow, the need for strong financial risk management practices within MFIs (e.g., in areas such as credit risk, treasury risk, and liquidity risk) is even more important to address potential unexpected risks, uncertainty, and shocks.[2]

Cost efficiency reflects how efficiently an MFI uses its resources to provide loans to its clients. Running operations efficiently is paramount to the success of MFIs in reaching their dual long-term objectives of outreach to the poor and financial sustainability (Yimga, 2018). Operational costs in the microfinance industry have been high compared to the traditional banking sector, representing around 30% of the average loan portfolio (Mersland et al., 2019; Mersland & Strøm, 2009). Although joint liability schemes have been introduced by MFIs in order to increase repayment (Armendáriz & Morduch, 2010), the actual loans granted have traditionally been unsecured or secured with low-value collateral, negatively affecting the quality of their portfolios.

Risk management is an important task for MFIs to find the right balance between risk and reward. In the present paper, we explore three of the most important financial risk management strategies of MFIs: asset quality, liquidity management, and solvency.[3] Credit risk is important for MFIs, as higher levels of credit risk could lead to solvency issues and ultimately to the default of the MFI. Recent technological innovations such as the provision of online services could also help reduce the production costs of loans and improve efficiency. Thus, cost efficient MFIs could be better positioned to offer lower interest rates to their clients and therefore expect higher repayment rates and portfolio quality. Therefore, our first hypothesis suggests that:

> **H1.** Cost efficiency is positively associated with MFIs' asset quality.

As documented in previous banking literature, moral hazard problems in credit markets are positively related to capital levels (Allen et al., 2011; Gropp & Heider, 2010). Previous studies in the banking sector regarding capital highlight its importance related to the survival probability of banks in two ways. First, capital plays a loss-absorption role because higher bank capital increases the buffers of banks against shocks to asset values (Repullo, 2004; Von Thadden, 2004). Second, it also serves as a role in reducing risk. According to incentive-based theories, higher bank capital strengthens the incentive of banks to monitor their relationships with borrowers (Holmstrom & Tirole, 1998) or reduces the excessive risk-taking incentives of banks (Acharya & Thakor, 2016).

However, literature investigating the determinants of the level of capital of MFIs is scarce. Bogan (2012) suggests that the capital structure of MFIs is related to their financial performance. Tchakoute Tchuigoua (2014) finds that institutional frameworks and the quality of institutions impact the capital structure of MFIs. Tchakoute Tchuigoua (2016) studies the impact of competition on capital for MFIs. More recently, Soumaré et al. (2020) uncover a negative relationship between MFI's capital-to-asset ratio and business cycle indicators. The effect of efficiency on capital is still an under-explored issue in the microfinance literature. More efficient MFIs are expected to have better monitoring technologies by using appropriate methodologies to assess client risk, which in turns allows them to enjoy lower production costs, higher profits, and a stronger capital position. In addition, low leverage (debt) along with high levels of equity capital could indicate a good capacity to absorb unexpected losses and a low dependence on external funds, which need to be repaid. We would expect that more efficient MFIs are more likely to be solvent (i.e., able to absorb unexpected losses), to meet their obligations, and therefore keep higher levels of equity. In short, our second hypothesis is formulated as follows:

H2. Cost efficiency is positively associated with higher levels of capital ratio.

Three theoretical foundations can describe the role of liquidity within a firm. First, transaction cost theory hypothesizes that firms hold additional cash to diminish exchange costs. Lack of adequate levels of cash to cover its debt, a firm may be compelled to borrow externally until it can liquidate its non-liquid assets, which generates additional interest expenses and transaction costs (Mun & Jang, 2015). Second, the free cash flow hypothesis (Jensen, 1986) notes that increased liquidity gives a wider pool of possibilities for managers to their own interests that eventually might lead to lower financial performance (Adusei, 2021). Third, the risk–return theory postulates that the risk of a financial asset is positively with its return. Liquid assets are less risky than their non-liquid counterparts. From this perspective, when an MFI keeps more liquid assets in order to reduce its liquidity risk, it may harm its financial performance by not using these resources to generate income from lending.

Evidence for banks suggests a positive link between liquid assets (free cash flows) and incentives to take additional risk (Acharya & Naqvi, 2012). There is mixed evidence on the relationship between efficiency and liquidity risk in the banking sector (Altunbas et al., 2000; Fiordelisi et al., 2011; Radić et al., 2012). Baltas et al. (2017) conduct the first combined theoretical and empirical study that links efficiency to liquidity. Through their proposed 'cost efficiency-liquidity creation hypothesis (CELCH)', the authors show that the cost efficiency gains derived from bank consolidation activity can result in increased liquidity.

In contrast to the significant amount of research conducted in the commercial banking sector, the analysis of financial risk management in the context of liquidity for MFIs is relatively under-explored. Maintaining adequate levels of liquidity is important to any MFI, as these institutions are more vulnerable to unexpected changes in the demand for deposits. MFI with inadequate liquidity might be less immune to future uncertainty, timely delay of refinancing, disruption in meeting growth projections, and increased portfolio at risk. Part of MFI's financial risk management practices is to ensure that sufficient liquid assets are timely available to meet current (expected and unexpected) payment obligations. A sign of the liquidity available to cover short-term liabilities can be measured using the core measure of liquid assets as the numerator and total assets as the denominator. Another useful indicator is the loans to deposit ratio (LDR), which measures the role of deposits as a funding source of loans. A high LDR implies that MFIs might not have enough liquidity to cover any unforeseen fund requirements (e.g., outflows because of larger deposit withdrawals from clients). MFIs are generally exposed to low levels of liquidity risk, as they tend to lend out short-term small-size loans and deposits are relatively small in size. Schulte and Winkler (2019) show that MFIs present a lower liquidity ratio than banks and, therefore, are less disposed to use liquid assets as liquidity buffers. Credit risk is also related to liquidity risks, as high non-repayment rates can create a loss of liquidity and even problems to borrow from external sources. The increasing importance of MFIs in specific geographical areas as only providers of financial services means that liquidity concerns can trigger a domino effect that affects the entire market in which they operate. We expect that cost efficient MFIs allocate excess liquidity even more efficiently and, therefore, require lower levels of liquid assets to meet their obligations. We aim to test this argument with the following third hypothesis:

H3. Cost efficiency is negatively associated with MFIs' liquidity position.

2.1 | Deposit mobilizing MFIs versus lending-only MFIs

MFIs have gradually extended the scope of the financial services they offer. This has had an essential impact on the microfinance industry. From providing credit-only financial services, MFIs have increased their provision of financial products (e.g., payment services, savings accounts, and insurance) to cover the needs of the disadvantaged population (Li et al., 2019). The provision of deposit services by MFIs is critical for their clients as it allows them to save, but also for MFIs as it provides them with the required funding to expand their loan portfolio. In addition, deposits can boost local development, as they provide a wider pool of funds, which can be used to finance productive investments. Having said that, not all MFIs provide deposit services because of regulatory constraints. In addition, providing deposit and other savings services is costly, as the small amount of savings per client is not always enough to cover production costs.

Providing financial services to poor customers can be costly for lending MFIs as well because of higher screening and monitoring costs (e.g., lack of previous financial information of potential borrowers) compared to commercial banks. Although MFIs have created strategies to reduce these costs (e.g., by providing group credit advances, making borrowers mutually responsible for the reimbursement of individual debt), the provision of lending services to the disadvantaged population is still more costly and riskier than offering the same services to wealthier clients (Hermes & Hudon, 2018). Therefore, in this study, we also contribute to the literature by shedding light on the relationship between efficiency and the type of MFIs according to the services they provide across all financial risk management indicators.

2.2 | For-profit MFIs versus not-for-profit MFIs

The switch towards the commercialization of microfinance was coupled with a change in the type of MFIs offering financial services. Although at first non-profit NGOs had the largest market segment, particularly from the mid-1990s, the number of for-profit MFIs has gradually increased over time (Li et al., 2019). Given that the provision of financial services to the poorer population is expensive, MFIs require a sustainable financial framework that would allow them to cover these costs and remain profitable. Socially orientated MFIs are generally funded by a combination of donations, external funds (e.g., equity and loans), and depending on their regulatory status from deposits as well. The relative significance of these funds may depend on the formal status (or type) of the MFIs. MFIs can be either not-for-profit non-governmental organizations (NGOs), cooperatives, non-banking financial institutions or (for-profit) shareholder-based financial institutions. The available pool of funds that MFIs have access to, in combination with the way these funds are utilized to offer financial services, eventually dictates their operations performance, risk strategy, and long-term goals. Ownership structure plays a crucial role in the governance of MFIs. Some argue that non-profit MFIs should convert into shareholder-held firms (SHFs) to benefit from more advanced corporate governance and regulation by banking authorities (Servin et al., 2012). However, Mersland and Strøm (2009) are opposed to this view and argue that SHFs and NGOs perform similarly in terms of social and financial targets. In this paper, we shed light on this debate by exploring how MFI profit-orientation could also affect the relationship between efficiency and financial risk management practices of MFIs.

3 | EMPIRICAL METHODOLOGY AND DATA

3.1 | Cost efficiency modelling

The aim of the present research is to empirically examine the relationship between cost efficiency and financial risk management of microfinance institutions. There is a large literature under the heading 'non-structural and structural approaches', which aims at testing the efficiency of financial intermediaries. The non-structural approach compares productivity and performance ratios among banks and considers how these ratios are related to investment strategies and banks' characteristics, such as the quality of a bank's governance or its product, among other factors. The structural approach usually relies on the economics of cost minimization or profit maximization, where the performance equation denotes a cost or a profit function. More recently, the optimization problem amounts to managerial utility maximization, where the manager trades-off risk and expected return. Given that many MFIs do not have a profit maximization scope, in this study, and in line with the MFI literature (Afrifa et al., 2019; Hartarska et al., 2013; Hermes et al., 2011; Tchakoute Tchuigoua, 2016), we consider the cost minimization strategy to allow for meaningful comparisons among all the MFIs in our sample.

As far as the structural performance equation is concerned, this can be fitted to the data as an average relationship which assumes that all banks are equally efficient at minimizing cost or maximizing profit, subject to a random error ε_i, that is assumed to be normally distributed. On the other hand, the structural performance equation can be estimated using a stochastic frontier approach (SFA) to capture best-practice and to gauge inefficiency (i.e., the difference between the best-practice performance and achieved performance). In the stochastic frontier, which was first developed by Aigner et al. (1977) and Meeusen and van den Broeck (1977), the error term ε_i consists of two components: a two-sided random error that represents noise [v] and a one-sided error representing inefficiency [u]. Thus, SFA's main advantage lies in separating the inefficiency that results from random shocks and the inefficiency of the firm itself. In addition, SFA models can be used to estimate errors and test hypotheses (Odeck & Bråthen, 2012). Another frontier technique to estimate efficiency is data envelopment analysis (DEA). However, econometricians have criticized DEA because in contrast with SFA it may confuse random variations in productivity with variations in efficiency (Rosko, 2001).[4] Moreover, DEA, is very sensitive to data, sample size, and measurement errors. In these cases, DEA leads to biased estimates (Fall et al., 2018; Greene, 1983).

Therefore, to avoid the aforementioned estimation issues, we follow previous microfinance studies in the literature (e.g., Hartarska et al., 2013; Hartarska & Mersland, 2012; Hermes et al., 2011; Zamore et al., 2021) and estimate the level of cost efficiency by using the stochastic frontier approach (SFA). In this setting, outputs and input prices are defined under the intermediation approach (Hermes et al., 2011; Hughes & Mester, 1998; Koetter et al., 2012; Sealey & Lindley, 1977).

We specify output as total loans (Q) and three input prices: the total operating expenses per employee (W_1) regarding labour, the financial expenses per total level of liabilities (W_2) with regards to financial capital and the ratio of expenses on fixed assets to total fixed assets (W_3) as far as the physical capital is concerned. Following Tchakoute Tchuigoua (2016) and Afrifa et al. (2019), we account for the loan portfolio quality (risk exposure of the MFI) by the value of all loans outstanding that have one or more instalments of principal past due more than 30 days (PAR30). As an additional control of the differences in risk-taking strategies among MFIs, we account for the size of the MFIs (proxied by total assets), in line with previous studies in the literature (Afrifa et al., 2019; Tchakoute Tchuigoua, 2016).[5]

The final specification of our cost stochastic frontier model takes the following translog function[6]:

$$
\begin{aligned}
\ln TC_{it} = {} & \beta_0 + \beta_Q \ln Q_{it} + \sum_{s=1}^{2} \beta_{ws} \ln W_{s,it} + \frac{1}{2}\beta_Q \ln Q_{it}^2 \\
& + \frac{1}{2}\sum_{s=1}^{2}\sum_{p=1}^{2} \beta_{wswp} \ln W_{s,it} \ln W_{p,it} \\
& + \sum_{s=1}^{2} \beta_{ws} \ln W_{s,it} \beta_Q \ln Q_{it} + \beta_{Par30} \mathrm{Par30}_{it} \\
& + \beta_{Size} \ln Size_{it} + \beta_T T + \frac{1}{2}\beta_T T^2 + v_{it} + u_{it},
\end{aligned}
$$

where the two-sided random error term v is assumed to follow a normal distribution around the frontier and u accounts for the firm's inefficiency and is assumed to follow a half-normal distribution (i.e., non-negative).

It should be noted that for the estimation of the cost frontier to develop appropriately, linear homogeneity in input prices must be imposed a priori. This requires:

$$\sum_{s=1}^{3} \beta_{ws} = 1.$$

Linear homogeneity restrictions are therefore imposed on all input prices and the dependent variable regarding the third input price (i.e., W_3).

As a second stage analysis, we analyse the impact of the efficiency scores computed above on the financial risk management of the MFIs. Specifically, we consider for the first time in the literature all three core areas of the financial risk management of MFIs (Ledgerwood et al., 2013), namely asset quality or credit risk, solvency and liquidity management.

3.2 | Panel-data models

We estimate the following panel-data models where efficiency is our key variable of interest. In addition, we estimate models to assess the differential effect across different types of MFIs, that is, deposit mobilizing and lending only MFIs, as well in terms of their profit orientation, that is, profit and non-profit MFIs:

$$\text{Financial Risk Management}_t = f(\text{Efficiency}_{t-1}, \text{Controls}_{t-1}) + \varepsilon_{i,t},$$

where the dependent variable (financial risk management) is proxied by asset quality (credit risk) indicators, solvency and liquidity. Control variables include Size (the natural logarithm of total assets), Return on equity (ROE), Financial revenue to total assets, type of MFI and year dummies. All our models included lagged independent variables to alleviate endogeneity concerns.[7] Table A1 in the Supplementary material provides detailed information of all variables used in the present study.

3.3 | Treatment effects: Average treatment effect on the treated (ATET) using propensity-score matching (PSM)

Determining a causal effect of cost efficiency on financial risk management of MFIs is complex due to potential confounding variables. The Average Treatment Effect on the Treated (ATET) combined with Propensity-Score Matching (PSM) offers a rigorous method to address this complexity. Propensity Score Matching (PSM) is a widely used method for estimating causal effects in observational studies (Dehejia & Wahba, 2002). PSM balances covariates between treatment and control groups by matching individuals with similar propensity scores, which represent the conditional probability of receiving treatment given observed covariates. PSM creates comparable groups for more accurate treatment effect estimation (Rosenbaum & Rubin, 1983). In this study, MFIs are classified into two distinct treatment groups based on their cost-efficiency within a specific geographical region where the MFI operates. The first group consists of MFIs with cost-efficiency higher than the median for that region. The second group encompasses MFIs that exceed the median cost-efficiency for all MFIs in that region for a given year.

PSM utilizes observed data to calculate the probability (propensity) of each MFI being in the treatment group based on its characteristics. By pairing treated MFIs with similar untreated ones using these propensity scores, we create a quasi-experimental setting that diminishes the influence of confounding variables. Each MFI is paired

TABLE 1 Summary statistics.

	Observations	Mean	Standard deviation	Min.	P25	Median	P75	Max.
Asset quality ratios								
PAR90	9197	0.041	0.063	0	0.006	0.023	0.049	0.43
Write-offs (WOFF)	9047	0.019	0.031	0	0	0.007	0.023	0.182
Risk coverage (RISK_COV)	8910	2.673	8.101	0	0.525	0.924	1.444	65.029
Renegotiated loans ratio (RLR)	8295	0.007	0.019	0	0	0	0.003	0.127
NPL30	8743	0.078	0.091	0	0.019	0.051	0.1	0.551
Loan loss reserve (LLRR)	10,038	0.041	0.039	0	0.015	0.031	0.054	0.243
Loan loss provision (LLPR)	10,121	0.023	0.032	−0.034	0.005	0.014	0.031	0.184
Liquidity ratios								
Liquid assets to total assets (LA/TA)	10,079	0.151	0.12	0.003	0.064	0.122	0.205	0.604
Loans to deposits (LDR)	5606	2.973	2.7	0.816	1.092	1.792	3.512	9.353
Capital ratios								
Debt to equity (D/E)	10,121	4.632	5.648	0.04	1.45	3.32	5.86	44.14
Equity to assets (E/A)	10,121	0.304	0.214	0.022	0.146	0.231	0.409	0.959
Uncovered capital (U_CAP)	8910	0.178	0.177	0.011	0.038	0.11	0.263	0.566
Cost-efficiency and control variables								
Cost efficiency (COST EFF)	8395	0.132	0.056	0.025	0.105	0.122	0.144	0.766
Ln size (SIZE_LN)	10,121	16.481	1.905	12.164	15.122	16.36	17.742	21.12
Return on equity (ROE)	10,109	0.069	0.311	−1.84	0.016	0.094	0.195	0.869
Financial revenue/total assets (F_REV)	10,120	0.266	0.128	0.063	0.179	0.235	0.323	0.739
Deposit taking (DEPOSIT TAKING)	9761	0.574	0.495	0	0	1	1	1
For-profit MFI (PROFIT)	9913	1.465	0.499	1	1	1	2	2

TABLE 2 Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) PAR90	1.000																	
(2) WOFF	0.202	1.000																
(3) RISK_COV	−0.162	−0.116	1.000															
(4) RLR	0.518	0.165	−0.093	1.000														
(5) NPL30	0.847	0.580	−0.197	0.443	1.000													
(6) LLRR	0.558	0.267	−0.014	0.257	0.550	1.000												
(7) LLPR	0.269	0.607	−0.083	0.124	0.495	0.472	1.000											
(8) LA/TA	0.116	0.048	0.017	0.014	0.123	0.161	0.091	1.000										
(9) LDR	−0.118	−0.001	0.036	−0.077	−0.106	−0.149	−0.002	−0.203	1.000									
(10) D/E	0.048	−0.059	0.030	0.020	0.001	0.017	−0.010	0.087	−0.132	1.000								
(11) E/A	0.013	0.097	−0.018	−0.019	0.055	0.025	0.030	−0.053	0.382	−0.586	1.000							
(12) U_CAP	0.613	0.176	−0.219	0.370	0.610	0.435	0.256	0.059	−0.260	0.425	−0.425	1.000						
(13) COST EFF	−0.048	−0.078	0.047	0.008	−0.077	−0.086	−0.118	−0.079	0.292	−0.181	0.468	−0.217	1.000					
(14) SIZE_LN	−0.030	0.033	0.004	0.120	−0.027	0.039	0.034	0.083	−0.285	0.143	−0.378	0.138	−0.101	1.000				
(15) ROE	−0.202	−0.219	0.055	−0.096	−0.242	−0.195	−0.264	−0.097	−0.026	−0.160	−0.013	−0.185	0.075	0.154	1.000			
(16) F_REV	−0.106	0.264	−0.014	−0.079	0.046	0.015	0.293	−0.192	0.228	−0.175	0.198	−0.127	−0.040	−0.242	0.094	1.000		
(17) DEPOSIT TAKING	0.056	−0.076	−0.045	−0.046	0.027	0.069	−0.022	0.234	−0.084	0.198	−0.335	0.247	−0.297	0.226	0.041	−0.224	1.000	
(18) PROFIT	−0.028	0.087	−0.010	0.020	0.031	−0.039	0.104	0.122	−0.024	0.047	−0.155	0.036	−0.066	0.261	0.040	0.088	0.079	1.000

TABLE 3 Asset (portfolio) quality ratios.

	PAR90	Write-offs	Risk coverage	Renegotiated loans ratio	NPL30	Loan loss reserve	Loan loss provision
Panel A: Panel regressions							
Cost efficiency$_{t-1}$	−0.031	−0.025**	2.368	0.010	−0.070	−0.064***	−0.049***
	(0.03)	(0.01)	(2.63)	(0.01)	(0.04)	(0.02)	(0.01)
Ln (assets)$_{t-1}$	0.002	0.003***	−0.288**	0.001***	0.006***	0.002***	0.004***
	(0.00)	(0.00)	(0.11)	(0.00)	(0.00)	(0.00)	(0.00)
ROE$_{t-1}$	−0.026***	−0.018***	1.224***	−0.006***	−0.051***	−0.016***	−0.008***
	(0.01)	(0.00)	(0.32)	(0.00)	(0.01)	(0.00)	(0.00)
Financial revenue/TA$_{t-1}$	−0.031**	0.056***	−1.142	−0.008**	0.037	0.017**	0.061***
	(0.01)	(0.01)	(1.43)	(0.00)	(0.02)	(0.01)	(0.01)
Type: Credit union/ cooperative	0.009	−0.001	−1.748***	−0.003	0.017*	−0.002	−0.003
	(0.01)	(0.00)	(0.57)	(0.00)	(0.01)	(0.00)	(0.00)
Type: NBFI	0.003	0.006**	−0.452	0.000	0.016*	0.000	0.005*
	(0.01)	(0.00)	(0.53)	(0.00)	(0.01)	(0.00)	(0.00)
Type: NGO	0.004	0.003	0.182	−0.001	0.011	0.003	0.002
	(0.01)	(0.00)	(0.63)	(0.00)	(0.01)	(0.00)	(0.00)
Type: Rural bank	0.030***	−0.001	−0.425	−0.002	0.072***	0.008	−0.006**
	(0.01)	(0.00)	(1.00)	(0.00)	(0.02)	(0.01)	(0.00)
Constant	0.015	−0.041***	6.866***	−0.015***	−0.048	0.004	−0.050***
	(0.02)	(0.01)	(2.18)	(0.01)	(0.04)	(0.01)	(0.01)
Observations	6540	6361	6430	5857	6282	6778	6808
R-squared (within)	0.054	0.050	0.009	0.034	0.074	0.045	0.038
R-squared (overall)	0.047	0.161	0.016	0.041	0.067	0.048	0.150
R-squared (between)	0.030	0.206	0.022	0.044	0.058	0.054	0.226
Wald Chi-Squared Test	152.84***	256.42***	65.80***	107.67***	180.86***	141.826***	269.640***
Panel B: Average treatment effect on the treated (ATET) using propensity-score matching (PSM)							
B1. ATET for cost efficiency	−0.694***	−0.322***	17.124	−0.132***	−1.120***	−0.852***	−0.445***
	(0.15)	(0.06)	(19.62)	(0.05)	(0.21)	(0.09)	(0.06)
B2. ATET for cost efficiency	−0.732***	−0.353***	−1.459	−0.122**	−1.165***	−0.907***	−0.472***
	(0.15)	(0.06)	(20.34)	(0.05)	(0.21)	(0.09)	(0.06)

Note: Panel A reports results for Random-effects panel regressions. The omitted category is 'Type: Bank'. All models include year fixed effects. Standard errors, shown in parentheses, are clustered at the MFI level. Panel B reports the average treatment effect on the treated (ATET), in percentage, in percentage, estimated using propensity-score matching (PSM). The control group in B1 consists of all MFIs with higher than median cost efficiency in the geographical region where the MFI is located. Meanwhile, the control group in B2 comprises all MFIs with higher than median cost efficiency in the same geographical region and the same year where the MFI is located. Abadie-Imbens (AI) robust standard errors are reported in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Definitions can be found in Appendix A in Supplementary material.

with 20 MFIs from the control group. Once this matching is done, the ATET measures the difference in outcomes between the treated group and their matched counterparts. This differential enables the isolation and estimation of the causal effect of the treatment on the MFIs in the treatment group. We present ATET estimations in conjunction with panel data findings to shed further light on the influence of cost efficiency on financial risk management.

3.4 | Data

Building on earlier empirical research in the field of microfinance, such as those conducted by Hartarska et al. (2011), Hermes et al. (2011), Tchakoute Tchuigoua (2014, 2016), Afrifa et al. (2019), and Liñares-Zegarra and Wilson (2018), we use the Microfinance Information Exchange (MIX) database which is freely accessible through the World Bank's Databank platform.

TABLE 4 Cost efficiency and asset (portfolio) quality ratios by deposit/lending MFIs.

	Deposit-mobilizing MFIs			Lending-only MFIs		
	Model 1: Panel regression	**Model 2: ATET**	**Model 3: ATET**	**Model 1: Panel regression**	**Model 2: ATET**	**Model 3: ATET**
PAR90	−0.228***	−1.189***	−1.463***	0.008	−0.312	−0.352
	(0.05)	(0.25)	(0.26)	(0.03)	(0.23)	(0.23)
Observations	3368	4340	4340	2955	3669	3669
R-squared (overall)	0.069			0.046		
Wald Chi-Squared Test	123.531***			140.59***		
Write-offs	−0.106***	−0.409***	−0.522***	−0.013	−0.277***	−0.290***
	(0.04)	(0.09)	(0.08)	(0.01)	(0.10)	(0.09)
Observations	3250	4102	4102	2929	3616	3616
R-squared (overall)	0.165			0.193		
Wald Chi-Squared Test	166.712***			192.73***		
Risk coverage	11.112	17.203	5.639	0.978	−41.234	−45.953
	(6.92)	(21.26)	(22.39)	(2.74)	(39.05)	(38.70)
Observations	3317	4253	4253	2910	3589	3589
R-squared (overall)	0.024			0.012		
Wald Chi-Squared Test	49.666***			39.67***		
Renegotiated loans ratio	−0.004	−0.064	−0.102*	0.004	−0.091	−0.122
	(0.01)	(0.05)	(0.06)	(0.01)	(0.07)	(0.08)
Observations	2987	3897	3897	2755	3424	3424
R-squared (overall)	0.076			0.038		
Wald Chi-Squared Test	86.139***			79.95***		
NPL30	−0.411***	−1.798***	−2.200***	−0.007	−0.766**	−0.823***
	(0.10)	(0.34)	(0.38)	(0.04)	(0.32)	(0.30)
Observations	3200	4102	4102	2907	3616	3616
R-squared (overall)	0.091			0.081		
Wald Chi-Squared Test	132.508***			142.95***		
Loan loss reserve	−0.168***	−0.948***	−1.008***	−0.030	−0.567***	−0.584***
	(0.04)	(0.14)	(0.15)	(0.02)	(0.15)	(0.13)
Observations	3502	4359	4359	3047	3712	3712
R-squared (overall)	0.067			0.050		
Wald Chi-Squared Test	121.239***			99.73***		
Loan loss provision	−0.142***	−0.607***	−0.584***	−0.036***	−0.389***	−0.350***
	(0.03)	(0.10)	(0.10)	(0.01)	(0.11)	(0.10)

TABLE 4 (Continued)

	Deposit-mobilizing MFIs			Lending-only MFIs		
	Model 1: Panel regression	Model 2: ATET	Model 3: ATET	Model 1: Panel regression	Model 2: ATET	Model 3: ATET
Observations	3512	4373	4373	3059	3727	3727
R-squared (overall)	0.157			0.186		
Wald Chi-Squared Test	218.267***			178.99***		

Note: Model 1 presents results from random-effects panel regressions. To shorten the size of the table, we report only the estimated coefficients for our main variable of interest, namely, cost efficiency. Every regression incorporates a full set of control variables and employs the same methodology as in Table 3. Estimates for all control variables are available upon request. Standard errors, displayed in parentheses, are clustered at the MFI level. Models 2 and 3 detail the average treatment effect on the treated (ATET), in percentage, estimated using propensity-score matching (PSM). The control group for Model 2 consists of all MFIs with a cost efficiency higher than the median in the geographical region where the MFI is based. In contrast, the control group for Model 3 includes all MFIs with a cost efficiency above the median in both the same geographical region and the same year where the MFI operates. Abadie-Imbens (AI) robust standard errors are presented in parentheses. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Definitions are provided in Appendix A in Supplementary material.

The MIX database offers a notable advantage, as the included MFIs are chosen primarily for their ability to deliver high-quality data (Bogan, 2012). Moreover, these MFIs collectively serve a substantial portion of microfinance clients worldwide.

Our final sample includes an unbalanced panel of 1326 MFIs over a 16-year period (2003–2018). The estimation period is longer than previous studies using the same database, such as Afrifa et al. (2019), which covers the period 2010–2015; but also, in line with other studies, such as Adusei (2021) that cover a 10-year period (2005–2014). We excluded observations with missing data (Hermes et al., 2011; Lozano-Vivas & Pasiouras, 2010), less than 3 observations for MFI, and negative, zero, or missing values for assets and equity. Following Berger and Mester (1997), Hartarska et al. (2013), and Liñares-Zegarra and Wilson (2018), all continuous variables are winsorized at the 1% of the distribution (top and bottom) to remove outliers in the data set.[8] Our sample composition consists of MFI banks (13.73%), Credit Unions/Cooperative (12.73%), NBFI (37.18%), NGOs (32.17%), and Rural Banks (4.19%). In terms of regional distribution, MFIs are located in Africa (13.61%), East Asia and the Pacific (11.64%), Eastern Europe and Central Asia (16.08%), Latin America and the Caribbean (36.05%), Middle East and North Africa (3.75%), and South Asia (18.87%). The distribution of our sample by MFI types and regions is available in Tables A2 and A3 in the Supplementary material.

Table 1 provides the summary statistics of all the variables in our study. Regarding asset quality ratios, the mean values are as follows: PAR90 (4.1%), Write-Offs (1.9%), Risk coverage (2.673), Renegotiated loans ratio (0.7%), NPL30 (7.8%), Loan loss reserve (4.1%), and Loan loss provision (2.3%). In terms of liquidity ratios and capital ratios, we observe the following mean values in our sample: Liquid assets to total assets (15%), Loans to deposits (2.973), Debt to equity (4.632), Equity to assets (30.4%), and uncovered capital (17.8%).

The mean value for cost efficiency is 0.132. Control variables exhibit the following mean values: Ln Size (16.481), Return on Equity (6.9%), Financial Revenue/Total Assets (26.6%), deposit taking (57.4%), and for-profit MFIs (1.465). In Table 2, we report pairwise correlations of all variables in our study. We also check for multicollinearity using the Variance Inflation Factor (VIF), obtained after estimating an OLS regression of the dependent variable against all control variables. The results reported in Table A5 in the Supplementary material show that all main explanatory variables have a Variance Inflation Factor (VIF) below the threshold of 10 (Afrifa et al., 2019; Wooldridge, 2012), suggesting there is no evidence of multicollinearity.

4 | EMPIRICAL FINDINGS AND DISCUSSION

4.1 | Asset quality

First, we present the results regarding the asset quality of MFIs. As shown in Table 3, the empirical evidence highlights that cost efficient MFIs exhibit lower levels of write-offs, loan loss reserves, and provisions in the panel estimations, but also lower levels of PAR90, write-offs, renegotiated loans, NPL30, loan loss reserves, and provisions based on the ATET estimations. Thus, our results provide support for our first hypothesis, stating that there is a positive relationship between cost efficiency and asset

TABLE 5 Cost efficiency and asset (portfolio) quality ratios by profit status.

	Not-for-profit MFIs			For-profit MFI		
	Model 1: Panel regression	Model 2: ATET	Model 3: ATET	Model 1: Panel regression	Model 2: ATET	Model 3: ATET
PAR90	−0.026	−0.475**	−0.592***	−0.040	−0.851***	−0.817***
	(0.03)	(0.21)	(0.21)	(0.06)	(0.25)	(0.24)
Observations	3574	4521	4521	2859	3608	3608
R-squared (overall)	0.040			0.073		
Wald Chi-Squared Test	70.395***			147.068***		
Write-offs	−0.021*	−0.306***	−0.395***	−0.052	−0.457***	−0.500***
	(0.01)	(0.08)	(0.08)	(0.04)	(0.12)	(0.13)
Observations	3468	4316	4316	2802	3491	3491
R-squared (overall)	0.080			0.263		
Wald Chi-Squared Test	151.782***			187.855***		
Risk coverage	0.815	63.321***	57.015**	8.437	−73.640*	−130.124***
	(2.66)	(23.32)	(25.33)	(5.87)	(41.56)	(44.98)
Observations	3484	4385	4385	2846	3573	3573
R-squared (overall)	0.027			0.028		
Wald Chi-Squared Test	35.788***			63.069***		
Renegotiated loans ratio	0.008	−0.008	−0.027	0.016	−0.222***	−0.246***
	(0.01)	(0.07)	(0.07)	(0.03)	(0.07)	(0.07)
Observations	3255	4136	4136	2510	3199	3199
R-squared (overall)	0.038			0.062		
Wald Chi-Squared Test	76.983***			116.102***		
NPL30	−0.061	−0.903***	−1.194***	−0.093	−1.448***	−1.485***
	(0.05)	(0.29)	(0.29)	(0.11)	(0.37)	(0.38)
Observations	3420	4316	4316	2771	3491	3491
R-squared (overall)	0.045			0.126		
Wald Chi-Squared Test	87.150***			167.723***		
Loan loss reserve	−0.052**	−0.532***	−0.626***	−0.112**	−0.980***	−0.981***
	(0.02)	(0.13)	(0.12)	(0.05)	(0.14)	(0.16)
Observations	3689	4537	4537	2981	3648	3648
R-squared (overall)	0.050			0.064		
Wald Chi-Squared Test	88.771***			85.508***		
Loan loss provision	−0.032***	−0.371***	−0.382***	−0.125***	−0.644***	−0.612***
	(0.01)	(0.08)	(0.08)	(0.04)	(0.11)	(0.12)

TABLE 5 (Continued)

	Not-for-profit MFIs			For-profit MFI		
	Model 1: Panel regression	**Model 2: ATET**	**Model 3: ATET**	**Model 1: Panel regression**	**Model 2: ATET**	**Model 3: ATET**
Observations	3711	4560	4560	2988	3660	3660
R-squared (overall)	0.091			0.215		
Wald Chi-Squared Test	230.170***			193.685***		

Note: Model 1 presents results from random-effects panel regressions. To shorten the size of the table, we report only the estimated coefficients for our main variable of interest, namely, cost efficiency. Every regression incorporates a full set of control variables and employs the same methodology as in Table 3. Estimates for all control variables are available upon request. Standard errors, displayed in parentheses, are clustered at the MFI level. Models 2 and 3 detail the average treatment effect on the treated (ATET), in percentage, estimated using propensity-score matching (PSM). The control group for Model 2 consists of all MFIs with a cost efficiency higher than the median in the geographical region where the MFI is based. In contrast, the control group for Model 3 includes all MFIs with a cost efficiency above the median in both the same geographical region and the same year where the MFI operates. Abadie-Imbens (AI) robust standard errors are presented in parentheses. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Definitions are provided in Appendix A in Supplementary material.

quality. Taken together, these results suggest that cost-efficient MFIs tend to exhibit fewer write-offs, suggesting their credit assessment procedures and monitoring systems might be superior. Additionally, these MFIs often have lower loan loss reserves, indicating fewer defaults or better risk assessment. This finding is further supported by their reduced loan loss provisions and reserves, which are used for potential future loan defaults. Furthermore, the lower PAR90 and NPL30 values observed among cost-efficient MFIs suggest a healthier loan portfolio, possibly because of enhanced monitoring mechanisms or lending practices. The decline in renegotiated loans observed in the ATET results implies that these MFIs might have more robust initial screening or efficient restructuring processes. In summary, results underscore the hypothesis that there exists a positive relation between cost efficiency and asset quality in MFIs. This suggests that cost-efficiency can translate to better risk management and, consequently, improved asset quality. As far as the size variable is concerned, we find that larger MFIs are more exposed to a higher amount of credit risk across all our panel-data models. We also observe that more profitable MFIs (in terms of ROE) exhibit higher levels of asset quality, except for risk coverage. Overall, our findings suggest a positive relationship between cost efficiency and the quality of MFIs assets. This is in line with previous studies in the banking literature that show that efficient banks exhibit lower levels of credit risk (e.g., Berger & DeYoung, 1997; Fiordelisi et al., 2011; Hughes & Mester, 1998; Kwan & Eisenbeis, 1996), which supports the bad management hypothesis (Berger & DeYoung, 1997; Williams, 2004). Moreover, with regards to the microfinance literature, our results corroborate those of Hartarska et al. (2013) who show that higher risk is associated with higher costs, while they are partially in line with those of Zamore et al. (2021), that document a non-linear relationship between credit risk and cost inefficiency.

Next, we distinguish between the risk management practices of MFIs that accept deposits (i.e., deposit-mobilizing MFIs) and those solely engaged in lending. Table 4 presents the estimated coefficients for our key variable of interest, which is cost efficiency, utilizing the same control variables as in Table 3. Results in Table 4 indicate that for deposit-mobilizing MFIs, higher levels of cost efficiency are associated with superior asset quality ratios (i.e., PAR90, Write-offs, NPL30, loan loss reserves, and loan loss provisions) across both panel regressions and ATETs. For MFIs that only lend, panel regressions point to a negative relationship between high-cost efficiency and loan loss provisions. ATET results support this finding, but also show that high levels of cost efficiency are associated with lower levels of write-offs, NPL30, and loan loss reserves. Results also suggest that while cost-efficient MFIs of both categories demonstrate improved risk management, the degree and economic impact seem more pronounced for MFIs that accept deposits, as evidenced by the magnitude of the estimated coefficients. This finding is consistent with that of Caudill et al. (2009) and Hartarska et al. (2013), documenting that MFIs relying more heavily on deposits are more cost-efficient over time. However, it contrasts with previous microfinance studies (e.g., Hartarska & Nadolnyak, 2007; Mersland & Strøm, 2009) that document that the type of organization (lending—only vs. deposit collecting) does not have an impact on MFI performance.

We have also investigated the differential impact of cost efficiency on MFI asset quality between profit and

TABLE 6 Solvency/capitalization ratios.

	Debt to equity (leverage)	Equity to assets	Uncovered capital
Panel A: Panel regressions			
Cost efficiency$_{t-1}$	−14.254***	1.490***	−0.474***
	(1.71)	(0.11)	(0.08)
Ln (assets)$_{t-1}$	0.388***	−0.041***	0.025***
	(0.10)	(0.00)	(0.00)
ROE$_{t-1}$	−2.809***	0.028***	−0.088***
	(0.52)	(0.01)	(0.01)
Financial revenue/TA$_{t-1}$	−2.774**	0.035	−0.034
	(1.08)	(0.04)	(0.03)
Type: Credit union/cooperative	0.299	−0.056***	0.093***
	(0.54)	(0.02)	(0.02)
Type: NBFI	−0.567	−0.002	0.035**
	(0.40)	(0.02)	(0.01)
Type: NGO	−0.076	0.004	0.024
	(0.49)	(0.02)	(0.02)
Type: Rural bank	1.841**	−0.141***	0.210***
	(0.72)	(0.02)	(0.03)
Constant	0.924	0.820***	−0.190***
	(1.92)	(0.08)	(0.06)
Observations	6808	6808	6430
R-squared (within)	0.047	0.112	0.084
R-squared (overall)	0.109	0.350	0.154
R-squared (between)	0.107	0.382	0.173
Wald Chi-Squared Test	258.42***	625.66***	354.28***
Panel B: Average treatment effect on the treated (ATET) using propensity-score matching (PSM)			
B1. ATET for cost efficiency	−1.925***	0.127***	−0.066***
	(0.13)	(0.00)	(0.00)
B2. ATET for cost efficiency	−1.929***	0.128***	−0.068***
	(0.13)	(0.00)	(0.00)

Note: Panel A reports results for Random-effects panel regressions. The omitted category is 'Type: Bank'. All models include year fixed effects. Standard errors, shown in parentheses, are clustered at the MFI level. Panel B reports the average treatment effect on the treated (ATET), in decimal format, estimated using propensity-score matching (PSM). The control group in B1 consists of all MFIs with higher than median cost efficiency in the geographical region where the MFI is located. Meanwhile, the control group in B2 comprises all MFIs with higher than median cost efficiency in the same geographical region and the same year where the MFI is located. Abadie-Imbens (AI) robust standard errors are reported in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Definitions can be found in Appendix A in Supplementary material.

non-profit MFIs. The empirical evidence presented in Table 5 shows that cost-efficient MFIs, regardless of their profit status, have lower levels of reserves and provisions according to both panel and ATET estimations. Interestingly, the estimated ATET reveals that cost-efficient MFIs, regardless of their profit orientation, have lower levels of PAR90, write-offs, renegotiated loans, and NPL30. While the results for risk coverage are positive for non-profit MFIs, the negative ATET coefficient indicates that for-profit MFIs might have better credit assessment and lending practices (i.e., fewer loans becoming overdue or needing renegotiation) as they become more cost-efficient. Consequently, if fewer loans are at risk, the MFI might not see the necessity to maintain high-risk coverage or to set aside large provisions for potential loan losses. The results also show that while cost-efficient MFIs from both categories (profit and non-profit) exhibit improved risk management, the degree and economic impact appear more pronounced for for-profit MFIs compared to their non-profit counterparts.

TABLE 7 Cost efficiency and solvency/capitalization ratios by deposit/lending MFIs.

	Deposit-mobilizing MFIs			**Lending-only MFIs**		
	Model 1: Panel regression	**Model 2: ATET**	**Model 3: ATET**	**Model 1: Panel regression**	**Model 2: ATET**	**Model 3: ATET**
Debt to equity (leverage)	−8.994**	−1.305***	−1.298***	−14.134***	−2.112***	−2.070***
	(4.49)	(0.18)	(0.19)	(2.09)	(0.19)	(0.19)
Observations	3512	4373	4373	3059	3727	3727
R-squared (overall)	0.067			0.092		
Wald Chi-Squared Test	101.725***			153.54***		
Equity to assets	1.345***	0.083***	0.087***	1.454***	0.142***	0.142***
	(0.21)	(0.01)	(0.01)	(0.13)	(0.01)	(0.01)
Observations	3512	4373	4373	3059	3727	3727
R-squared (overall)	0.257			0.292		
Wald Chi-Squared Test	215.996***			327.75***		
Uncovered capital	−0.836***	−0.056***	−0.067***	−0.336***	−0.049***	−0.049***
	(0.16)	(0.01)	(0.01)	(0.07)	(0.01)	(0.01)
Observations	3317	4253	4253	2910	3589	3589
R-squared (overall)	0.151			0.099		
Wald Chi-Squared Test	255.342***			237.27***		

Note: Model 1 presents results from random-effects panel regressions. To shorten the size of the table, we report only the estimated coefficients for our main variable of interest, namely, cost efficiency. Every regression incorporates a full set of control variables and employs the same methodology as in Table 3. Estimates for all control variables are available upon request. Standard errors, displayed in parentheses, are clustered at the MFI level. Models 2 and 3 detail the average treatment effect on the treated (ATET), in decimal format, estimated using propensity-score matching (PSM). The control group for Model 2 consists of all MFIs with a cost efficiency higher than the median in the geographical region where the MFI is based. In contrast, the control group for Model 3 includes all MFIs with a cost efficiency above the median in both the same geographical region and the same year where the MFI operates. Abadie-Imbens (AI) robust standard errors are presented in parentheses. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Definitions are provided in Appendix A in Supplementary material.

This observation is supported by the magnitude of the estimated coefficients. The results contribute to the existing literature (Galema et al., 2012), showing that non-profit MFIs are more likely to engage in excessive risk-taking due to the higher incentives of for-profit MFI shareholders to monitor management activities. Overall, our primary hypothesis (H1) is thus largely supported based on the previous empirical results.

4.2 | Solvency and capitalization

We now discuss the results related to solvency and capitalization. The empirical evidence presented in Table 6 indicates that there exists a strong relationship between cost efficiency and all three measures of capitalization and solvency, namely the debt-to-equity ratio, equity-to-asset ratio, and uncovered capital, as evidenced by both panel and ATET estimations. Specifically, the results suggest that cost-efficient MFIs have a stronger equity-to-debt ratio (lower leverage), higher equity-to-asset ratios, and lower levels of uncovered capital, which confirms our second hypothesis (H2). This is in line with Berger and DeYoung (1997), Williams (2004), and Fiordelisi et al. (2011), who report that more efficient banks become better capitalized. Our findings also contribute to the strand of literature (Boyd & De Nicolo, 2005; Martinez-Miera & Repullo, 2010; Tchakoute Tchuigoua, 2016) that highlights the importance of higher capitalization in cases of lower loan portfolio quality. The results of our analysis suggest that higher profitability (ROE) is associated with better levels of solvency and capitalization, while financial revenues correlate with lower leverage levels. In addition, we observe that rural banks exhibit higher leverage and lower capital levels compared to those of MFI-banks.

Next, we examine whether the relationship between efficiency and capital ratios varies based on whether

TABLE 8 Cost efficiency and solvency/capitalization ratios by profit status.

	Not-for-profit MFIs			For-profit MFIs		
	Model 1: Panel regression	Model 2: ATET	Model 3: ATET	Model 1: Panel regression	Model 2: ATET	Model 3: ATET
Debt to equity (leverage)	−12.909***	−2.122***	−2.058***	−17.262***	−1.167***	−1.108***
	(1.82)	(0.19)	(0.18)	(3.31)	(0.18)	(0.17)
Observations	3711	4560	4560	2988	3660	3660
R-squared (overall)	0.083			0.184		
Wald Chi-Squared Test	166.894***			198.386***		
Equity to assets	1.381***	0.143***	0.142***	1.820***	0.083***	0.091***
	(0.11)	(0.01)	(0.01)	(0.21)	(0.01)	(0.01)
Observations	3711	4560	4560	2988	3660	3660
R-squared (overall)	0.334			0.363		
Wald Chi-Squared Test	406.855***			330.605***		
Uncovered capital	−0.404***	−0.066***	−0.069***	−0.698***	−0.047***	−0.050***
	(0.08)	(0.01)	(0.01)	(0.16)	(0.01)	(0.01)
Observations	3484	4385	4385	2846	3573	3573
R-squared (overall)	0.146			0.183		
Wald Chi-Squared Test	196.870***			239.609***		

Note: Model 1 presents results from random-effects panel regressions. To shorten the size of the table, we report only the estimated coefficients for our main variable of interest, namely, cost efficiency. Every regression incorporates a full set of control variables and employs the same methodology as in Table 3. Estimates for all control variables are available upon request. Standard errors, displayed in parentheses, are clustered at the MFI level. Models 2 and 3 detail the average treatment effect on the treated (ATET), in decimal format, estimated using propensity-score matching (PSM). The control group for Model 2 consists of all MFIs with a cost efficiency higher than the median in the geographical region where the MFI is based. In contrast, the control group for Model 3 includes all MFIs with a cost efficiency above the median in both the same geographical region and the same year where the MFI operates. Abadie-Imbens (AI) robust standard errors are presented in parentheses. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Definitions are provided in Appendix A in Supplementary material.

MFIs take deposits, specialize solely in loan provision, and on the differences in profit-orientation (i.e., not-for-profit vs. for-profit). The results presented in Tables 7 and 8 reveal no significant differences in the direction of the relationship between cost efficiency and solvency, whether comparing deposit-mobilizing to lending-only MFIs or not-for-profit to for-profit MFIs. This finding is contrary to that of the study by Afrifa et al. (2019), which argues that MFIs holding capital ratios above the optimal level are less efficient. However, the magnitude of the effect tends to be larger for lending-only and for-profit MFIs compared to their deposit-mobilizing and not-for-profit counterparts.

4.3 | Liquidity management

The last set of results examines financial risk management indicators related to liquidity. Results from both panel and ATET estimations in Table 9 suggest that cost-efficient MFIs are associated with lower levels of liquidity, in line with our third hypothesis (H3). Cost-efficient MFIs are more likely to be active in the lending market and hold fewer liquid assets, as indicated by the positive estimated coefficient for the loan-to-deposit ratio. This is in line with the findings of Altunbas et al. (2000) and Radić et al. (2012), which document that efficient banks tend to have lower loan-to-asset ratios and lower liquidity ratios. The results also highlight that MFIs with substantial financial revenues tend to hold lower levels of liquidity. Furthermore, our analysis reveals that Credit Unions/Cooperatives, NBFIs, and NGO MFIs typically maintain lower liquid asset-to-total asset ratios compared to MFI-banks.

Finally, we examine whether the relationship between cost efficiency and liquidity depends on whether MFIs take deposits or specialize in lending. Results in Table 10 suggest that cost-efficient deposit-mobilizing

TABLE 9 Liquidity management ratios.

	Liquid assets to total assets	Loans to deposits
Panel A: Panel regressions		
Cost efficiency$_{t-1}$	−0.104*	27.319***
	(0.06)	(3.16)
Ln (assets)$_{t-1}$	0.003	−0.303***
	(0.00)	(0.09)
ROE$_{t-1}$	−0.010*	0.039
	(0.01)	(0.17)
Financial revenue/TA$_{t-1}$	−0.087***	2.049**
	(0.02)	(0.80)
Type: Credit union/cooperative	−0.057***	−1.033***
	(0.01)	(0.29)
Type: NBFI	−0.055***	1.319***
	(0.01)	(0.29)
Type: NGO	−0.060***	1.219***
	(0.01)	(0.35)
Type: Rural bank	0.034**	−1.787***
	(0.02)	(0.33)
Constant	0.202***	4.036***
	(0.04)	(1.55)
Observations	6798	3518
R-squared (within)	0.027	0.120
R-squared (overall)	0.089	0.306
R-squared (between)	0.094	0.361
Wald Chi-Squared Test	215.20***	423.01***
Panel B: Average treatment effect on the treated (ATET) using propensity-score matching (PSM)		
B1. ATET for cost efficiency	−0.020***	1.371***
	(0.00)	(0.09)
B2. ATET for cost efficiency	−0.020***	1.343***
	(0.00)	(0.09)

Note: Panel A reports results for Random-effects panel regressions. The omitted category is 'Type: Bank'. All models include year fixed effects. Standard errors, shown in parentheses, are clustered at the MFI level. Panel B reports the average treatment effect on the treated (ATET), in decimal format, estimated using propensity-score matching (PSM). The control group in B1 consists of all MFIs with higher than median cost efficiency in the geographical region where the MFI is located. Meanwhile, the control group in B2 comprises all MFIs with higher than median cost efficiency in the same geographical region and the same year where the MFI is located. Abadie-Imbens (AI) robust standard errors are reported in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Definitions can be found in Appendix A in Supplementary material.

MFIs are associated with lower levers of liquidity in line with our third hypothesis (H3). However, results for lending-only MFIs are mixed, depending on the estimation method used, which indicates the potential influence of other underlying factors not captured in this analysis or the presence of methodological sensitivities that warrant further investigation. Our empirical evidence adds to the study of Schulte and Winkler (2019) that reports that due to MFIs low level of liquid assets their management is less inclined to excessive lending via distortion of their liquidity. Finally, taking into account the profit orientation of MFIs, the results presented in Table 11 indicate that there is a positive and statistically significant relationship between cost efficiency and the loan-to-deposit ratio for both for-profit and not-for-profit MFIs. However, it appears that lower levels of liquidity are specifically associated with cost-efficient for-profit MFIs. In a similar vein, our findings offer additional insights into the life cycle theory and profit-incentive theory, discussing the conditions under which MFIs should employ specific types of funding vehicles (Bogan, 2012).

5 | CONCLUDING REMARKS

MFIs play a significant role in many countries as providers of financial services to the poor. In this study, we analyse for the first time the relationships between cost efficiency and financial risk management practices of MFIs, using a worldwide sample of MFIs. Our results suggest that more efficient MFIs are associated with better financial risk management practices across all three core areas of financial management: asset quality, capital, and liquidity. Specifically, we find that cost efficient MFIs are associated with better asset quality indicators, which in turn could suggest the presence of improved screening and monitoring mechanisms during the lending process. Moreover, our findings suggest that cost efficient MFIs are associated with higher levels of lending activity, while holding fewer liquid assets. Finally, we find that higher levels of cost efficiency are associated with higher capital levels and solvency. We do not find substantial differences in the effect of cost efficiency on capital-based indicators for deposit-mobilizing and lending-only MFIs or for-profit and not-for-profit MFIs. However, the impact of cost efficiency on asset quality appears to be stronger for deposit-mobilizing MFIs compared to lending-only MFIs.

By exploring the effects of cost efficiency on financial risk management practices for MFIs, our paper presents new evidence that could help to understand the effects of

TABLE 10 Cost efficiency and liquidity management ratios by deposit/lending MFIs.

	Deposit-mobilizing MFIs			Lending-only MFIs		
	Model 1: Panel regression	**Model 2: ATET**	**Model 3: ATET**	**Model 1: Panel regression**	**Model 2: ATET**	**Model 3: ATET**
Liquid assets to total assets	−0.711***	−0.037***	−0.037***	0.113**	−0.008**	−0.007**
	(0.11)	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)
Observations	3508	4366	4366	3054	3716	3716
R-squared (overall)	0.131			0.026		
Wald Chi-Squared Test	218.385***			66.64***		
Loans to deposits	27.399***	1.371***	1.335***			
	(3.16)	(0.09)	(0.09)			
Observations	3512	4373	4373			
R-squared (overall)	0.306					
Wald Chi-Squared Test	417.623***					

Note: Model 1 presents results from random-effects panel regressions. To shorten the size of the table, we report only the estimated coefficients for our main variable of interest, namely, cost efficiency. Every regression incorporates a full set of control variables and employs the same methodology as in Table 3. Estimates for all control variables are available upon request. Standard errors, displayed in parentheses, are clustered at the MFI level. Models 2 and 3 detail the average treatment effect on the treated (ATET), in decimal format, estimated using propensity-score matching (PSM). The control group for Model 2 consists of all MFIs with a cost efficiency higher than the median in the geographical region where the MFI is based. In contrast, the control group for Model 3 includes all MFIs with a cost efficiency above the median in both the same geographical region and the same year where the MFI operates. Abadie-Imbens (AI) robust standard errors are presented in parentheses. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Definitions are provided in Appendix A in Supplementary material.

TABLE 11 Cost efficiency and liquidity management ratios by Profit status.

	Not-for-profit MFIs			For-profit MFIs		
	Model 1: Panel regression	**Model 2: ATET**	**Model 3: ATET**	**Model 1: Panel regression**	**Model 2: ATET**	**Model 3: ATET**
Liquid assets to total assets	−0.040	−0.003	−0.003	−0.308*	−0.038***	−0.034***
	(0.05)	(0.00)	(0.00)	(0.17)	(0.00)	(0.00)
Observations	3705	4546	4546	2984	3656	3656
R-squared (overall)	0.035			0.125		
Wald Chi-Squared Test	98.724***			123.569***		
Loans to deposits	19.288***	n.e.	n.e.	38.302***	n.e.	1.582***
	(4.00)			(6.72)		(0.15)
Observations	1792			1671		2052
R-squared (overall)	0.244			0.356		
Wald Chi-Squared Test	261.927***			235.308***		

Note: Model 1 presents results from random-effects panel regressions. To shorten the size of the table, we report only the estimated coefficients for our main variable of interest, namely, cost efficiency. Every regression incorporates a full set of control variables and employs the same methodology as in Table 3. Estimates for all control variables are available upon request. Standard errors, displayed in parentheses, are clustered at the MFI level. Models 2 and 3 detail the average treatment effect on the treated (ATET), in decimal format, estimated using propensity-score matching (PSM). The control group for Model 2 consists of all MFIs with a cost efficiency higher than the median in the geographical region where the MFI is based. In contrast, the control group for Model 3 includes all MFIs with a cost efficiency above the median in both the same geographical region and the same year where the MFI operates. Abadie-Imbens (AI) robust standard errors are presented in parentheses. The abbreviation 'n.e.' refers to 'not estimable', indicating that Stata cannot calculate the ATET estimates due to perfect predictors in the treatment model. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Definitions are provided in Appendix A in Supplementary material.

the Covid-19 pandemic on financial risk management of MFIs. This is because there has been an increase in vulnerable clients (households) who also exhibit a higher risk of failing to meet their debt obligations (credit risk); but also pressures for MFIs in providing liquidity (liquidity risk) and remain solvent (capital risk).

Our study presents some limitations that are useful starting points for future research should availability of data emerges. Specifically, there is unfortunately limited availability of adequate indicators to measure the same types of risks faced by commercial banks (e.g., operational risks, reputational risks, compliance risks, etc.). Moreover, reporting of accounting data by MFIs is not as extensive compared to commercial banks. Because of this, to the best of our knowledge, CAMELS-style metrics are not available for MFIs in a cross-country setting. Therefore, depending on the availability of new data in specific countries, building CAMELS-style ratings for specific MFIs would be a worthwhile avenue for future research.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to disclose.

DATA AVAILABILITY STATEMENT

The data that supports the findings of this study is freely accessible through the World Bank's Databank platform at https://datacatalog.worldbank.org/dataset/mix-market.

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ENDNOTES

[1] Literature on measuring efficiency in the context of MFIs has mainly focused on cost efficiency (Hermes et al., 2011).

[2] We would like to thank an anonymous referee for suggesting including this important discussion.

[3] Financial management also includes the management of financial risks, including asset quality, capital adequacy (solvency), asset-liability management (ALM), and liquidity management (Ledgerwood et al., 2013). However, ALM management is not covered in the current paper due to lack of appropriate metrics.

[4] We thank an anonymous referee for this suggestion.

[5] The selection of both the dependent and independent variables is consistent with several other studies in the literature (e.g., Afrifa et al., 2019; Berger & Mester, 1997; Hermes et al., 2011; Hartarska et al., 2013; Tchakoute Tchuigoua, 2016). The sample used for estimation excludes any observations with negative, zero, or missing values for the variables TC, Q, W_1, W_2, and W_3.

[6] The translog function has been widely applied in the literature due to its flexibility. Berger and Mester (1997) found that both the translog and the Fourier-flexible form specifications yielded essentially the same average level and dispersion of measured efficiency, and both ranked the individual banks in almost the same order.

[7] We conduct Granger panel causality tests to check whether a bidirectional causality exist between financial risk management proxies and cost efficiency. We implement a test developed by Juodis et al. (2021) for testing the null hypothesis of no Granger causality. The null hypothesis that risk does not Granger-cause efficiency can't be rejected at the 1% level of significance. Results are available in Table A4 in the Supplementary material. We thank an anonymous referee for this suggestion.

[8] The sole exceptions are the variables 'Loans to Deposits' and 'Uncovered Capital', which are winsorized at the top and bottom 10% of the distribution to eliminate outliers in the dataset.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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