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Is donation funding a dilemma for microfinance institutions? ☆

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ABSTRACT

Microfinance institutions (MFIs) play critical roles in providing financial access to low-income communities worldwide. Yet, reliance on donation funding in the operations poses fundamental challenges to their long-term sustainability. We argue that this dependence creates an unclear agency relationship between donors (principal) – providing cost-free funds – and the MFI managers (agent), heightening moral hazard concerns. Also, due to the nature of the business model, MFIs' operating leverage increases as they increasingly expand lending operations with more cost-free donation funds. Based on a global dataset of 2653 MFIs across 119 countries over 20 years, we find that greater reliance on donations weakens MFIs' financial stability and reduces their likelihood of survival in the long run. The destabilizing effect intensifies over time, confirming the ex-post inefficiency of donation-reliant models. Our findings are robust across multiple empirical techniques and consistent across various dimensions such as profit orientation, legal status, geography, and country characteristics. By jointly examining financial stability and institutional survival, the study provides a comprehensive assessment of the long-term risks of donation dependence. These findings have important implications for donor agencies and policymakers in re-evaluating the effectiveness of the donation-based microfinance and in designing measures to promote sustainable models.

1. Introduction

Microfinance has evolved significantly over the last five decades since the concept was pioneered in 1976 by Nobel Laureate Muhammad Yunus. During this period, microfinance institutions (MFIs) have radically reshaped the global financial landscape, becoming an integral component of the financial system in many countries that have adopted this unique business model. Although

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MFIs have contributed to the financial inclusion of marginalized people,¹ their viability as a sustainable business model remains controversial.² The inherent goal of MFIs is to enhance financial inclusion through innovative financial models, but they may underestimate the risks in financial intermediation (López & Winkler, 2019). Hence, growing concerns over MFIs' struggles for survival (Ray, 2017; Sharma, 2011) might compromise their support for disadvantaged communities and their attenuation of poverty (Hickel, 2015).

The question of sustainability extends beyond the well-studied realm of loan operations (Banerjee et al., 2016, 2013; Dahal & Fiala, 2020; Rajbanshi et al., 2015; Roodman & Morduch, 2014) and into the relatively underexplored area of funding mechanisms. MFIs often rely heavily on external funding, particularly donations, to finance their operations and expand outreach³ – less than 30 % of MFIs are operationally sustainable, and the remaining 70 % depend on subsidies to cover the costs of financing and distributing loans (D'Espallier et al., 2013). Thus, donations remain a fundamental element of their business model (Afrifa et al., 2019; D'Espallier et al., 2013), despite the multiple phases of the institutional transformation of MFIs that have occurred since their inception (Copestake, 2007). Primarily, donations are meant to alleviate the financial distress of the poorer sectors of society. However, the microfinance business model has changed the nature of their financial allocations – MFIs rely considerably on donations for microloan disbursements (Minton & Schrand, 1999; Schaeck & Cihák, 2012; Tchuigoua, 2014). Donations, while essential for expanding access to financial services, may pose challenges to long-term stability. These challenges are rooted in several structural and managerial dynamics that require closer examination.

If we focus on the challenges through the theoretical lens of agency problems in the context of MFIs, the relationship between donors (principals) and MFI managers (agents) often lacks the accountability mechanisms typical of commercial financial arrangements. Unlike investors or lenders who actively monitor the use of their funds, donors often provide financial support without stringent oversight or performance-based conditions (Afrifa et al., 2019). This lack of oversight from donors creates opportunities for moral hazard, where MFI managers may allocate resources inefficiently or pursue objectives misaligned with donor intentions. For example, donations might be used to subsidize unsustainable lending practices or fund operational activities without clear performance metrics, potentially compromising the financial health of the institution. Moreover, donations can introduce uncertainty into the revenue streams of MFIs. Unlike earned income from interest payments or fees, donations are often inconsistent and subject to external factors such as donor priorities, economic conditions, or geopolitical events (Chen, 2015). This unpredictability makes it challenging for MFIs to plan long-term strategies, invest in capacity-building, or manage risks effectively. As a result, reliance on donations may expose MFIs to financial instability, particularly during periods of economic downturn or donor retrenchment.

Another issue linked to donation-based funding models is the potential for increased operating leverage. Unlike the traditional banking model, MFIs distribute the donations they receive as cost-free funds, because it is a one-way transfer from which the saver units (donors) do not expect financial returns. Ideally, donations are intended to make microfinance loans cheaper; however, evidence suggests that the interest rate is higher than that of traditional bank loans (Gonzalez, 2010a). Donations enable MFIs to expand their lending activities, which often leads to higher fixed costs in operations due to the unique nature of the business model (Gonzalez, 2010a; Mersland and Strøm, 2012). However, with the advantage of cost-free donations as a funding source, if the MFIs' lending operations (i.e., loan disbursements and monitoring) necessitate above-average interest charges, we need to investigate the soundness of these financial institutions.

The existing literature provides limited insights into the impact of funding structures on the sustainability of MFIs. Most studies focus on the left-hand side of MFIs' balance sheets – loan operations. Researchers have extensively analyzed the effectiveness of loan disbursement, social monitoring, and recovery mechanisms, often highlighting the sector's success in maintaining high repayment rates and reaching underserved populations (Chakravarty & Pylypiv, 2015; D'Espallier et al., 2013; Uddin et al., 2022). In coherence, several studies focus on MFIs' efficiency and performance (Assefa et al., 2013; Cull et al., 2007; Hermes et al., 2011, 2018; Hossain et al., 2020; Strøm et al., 2014; Zamore et al., 2021). However, the right-hand side of the balance sheet, which encompasses funding sources of MFIs' operations, remains unexplored. The right-hand side of the balance sheet is critical because funding decisions directly influence the financial sustainability of MFIs. A funding model reliant on donations may discourage MFIs from developing alternative revenue streams or pursuing efficiency gains, thereby perpetuating financial vulnerabilities (López & Winkler, 2019; Ray, 2017). Besides, the lack of accountability to donors may exacerbate inefficiencies, as managers face minimal pressure to optimize resource allocation or demonstrate measurable outcomes. This gap represents a significant limitation in understanding the broader dynamics of MFIs' business models. Furthermore, while previous studies have explored the impacts of subsidies broadly (e.g., Hudon & Traca, 2011; Cozarenco et al., 2022) or examined financial sustainability through the lens of client composition (e.g., D'Espallier et al., 2013), limited research has isolated donations as a unique funding source to analyze their implications on financial stability. These studies primarily focus on how subsidies, including donations, can lead to operational inefficiencies in MFIs. Our study fills this gap by investigating whether reliance on donations exposes MFIs to systemic financial risks, potentially threatening their long-term sustainability.

Given these dynamics, we investigate whether and how the reliance on donations affects the financial sustainability of MFIs. Specifically, we seek to understand whether the business model matters to the sustainability of MFIs. To provide robust empirical evidence, we utilize a global dataset containing 2653 MFIs from 119 countries from 1999 to 2018. Our findings show that donations negatively affect MFIs' financial stability. We also test the variations in donations and the stability of this relationship across several

¹ See Appendix A for details on the general operations of MFIs.

² See Appendix B for some relevant cases.

³ Outreach refers to the profile of MFI borrowers in terms of their poverty level and indicates how poor the clients are (Conning, 1999).

sub-samples, and the effect of donations on MFI stability remains negative. Furthermore, we investigate how donations contribute to the survival (or failure) of MFIs, considering the close association between financial institution stability and survival. Consistent with the stability analyses, we find that donations significantly enhance MFIs' likelihood of failure; the higher the value of donations received, the greater the probability of liquidation. Our findings are consistent across different estimation methods: ordinary least squares (OLS), panel fixed effects (FE), and generalized method of moments (GMM). We confirm the consistency of our empirical findings using further robustness tests, including a median-based quantile regression, two-stage least squares (2SLS) to correct for endogeneity, and the Heckman two-stage method to correct for sample selection bias that may arise in econometric estimations. Hence, we generally assert that donations received by MFIs that are used to support their business operations make them financially unstable and contribute to the likelihood of their failure.

Our study contributes to the literature in several ways. First, we provide theoretical insight by analyzing the impact of funding structures on MFI sustainability, drawing on concepts such as agency relationships, information asymmetry, moral hazard, and operating leverage. By applying these theoretical lenses, we offer a deeper understanding of the challenges associated with donation-based funding models, contributing to a more focused insight into the challenges facing the microfinance sector. This exploration is particularly relevant in the current context, where MFIs are increasingly expected to operate as sustainable enterprises while fulfilling their social mission of enhancing financial inclusion. Second, we present empirical evidence on the relationship between donations and financial stability, using a global dataset that addresses a critical gap in the literature, which has largely focused on loan operations and outreach while neglecting the financial dynamics of funding structures. Hence, we contribute to the current body of literature that investigates the crucial aspects of MFIs' financial stability, economic soundness, solvency, and vulnerability (Krauss & Walter, 2009; Schulte & Winkler, 2019; Wagner, 2012; Wagner & Winkler, 2013). Third, we extend the literature by linking the concepts of financial stability and institutional survival by jointly analyzing these outcomes; we demonstrate how donation reliance not only undermines near-term financial resilience but also jeopardizes the long-term viability of MFIs. Finally, the study extends the understanding of the role of the unique business model of MFIs (Uddin et al., 2022) from their stability and survival perspectives.

In addition to its contribution to the literature, our findings have significant implications for policymakers, donors, and MFI managers. For policymakers, the results highlight the need for regulatory frameworks that balance borrower protection with the financial health of MFIs, denoting the importance of supervisory frameworks that address the risks associated with high operating leverage and inconsistent funding sources. More specifically, our study points to the need for a more structured regulatory approach that explicitly considers the volatility of donation-based funding in stress-testing and stability oversight. For donors, the results underscore the need for more robust monitoring mechanisms to ensure the efficient allocation of funds and underline the importance of accountability mechanisms and performance-based funding models to ensure efficient resource allocation. In particular, we recommend that donors consider hybrid funding models that balance social objectives with institutional sustainability, helping MFIs transition from short-term dependency to long-term viability. For MFI managers, the findings emphasize the need to diversify funding sources and adopt strategies that enhance financial resilience. This includes building stable revenue streams, reducing excessive reliance on cost-free capital, and implementing stronger internal governance to mitigate moral hazard risks tied to donation flows. By addressing these issues, this research contributes to safeguarding the stability of the microfinance sector, ensuring its continued role in promoting financial inclusion and economic growth (Creel et al., 2015; Hannig & Jansen, 2011).

The rest of the paper is organized as follows: Section 2 highlights the theoretical insights, outlines the conceptual arguments, and specifies the study hypotheses. Section 3 presents the variables and test model specifications. Section 4 describes the study sample and data. Section 5 presents the empirical findings and discusses the results. Finally, Section 6 concludes the paper and offers suggestions for future research.

2. Theoretical insights, conceptual analysis, and hypotheses

In this section, we lay the conceptual and theoretical groundwork for our study by integrating key perspectives on financial intermediation, funding structures, and institutional risk. We first outline the theoretical foundations that explain the role of financial intermediaries, particularly MFIs, in mitigating information asymmetry and facilitating financial inclusion. We also highlight the agency problems that can emerge when external donations are not effectively monitored. In the second part, we develop a conceptual understanding of how the transformation of donation-based funding into lending activities shapes the operational dynamics of MFIs, revealing the potential trade-offs between outreach and financial sustainability. Finally, we advance to formulate two testable hypotheses that reflect the core contention of this study.

2.1. Theory insights

The role of financial intermediaries is central to the efficient functioning of an economy, as they channel funds from surplus units to deficit units. According to financial intermediation theory (Allen & Santomero, 1997; Diamond, 1984; Leland & Pyle, 1977), these intermediaries act as agents for lenders, screening and monitoring borrowers to reduce the risks arising from information asymmetry. This process mitigates the information asymmetry that typically arises in lending relationships, enabling lenders to make more informed decisions about the viability of investments (Carrasco & Salgado, 2014). Historically, financial intermediation was characterized by traditional banking operations, where banks collected deposits from individuals and provided loans to borrowers. However, the scope of financial intermediation has expanded over time, especially in the context of inclusive finance.

Traditional banks, for example, often exclude marginalized populations from accessing credit due to their perceived risk, lack of collateral, and the additional costs involved in serving them (de Aghion & Morduch, 2005; Ledgerwood, 1998; Morduch, 1999). These

exclusions are symptomatic of a market failure, where information asymmetry leads to adverse selection, with banks preferring borrowers who offer collateral and reducing lending to those without it. This practice limits financial access and, consequently, economic development, as it restricts opportunities for poverty alleviation (Demirgüç-Kunt et al., 2008). In contrast, MFIs have emerged to address this gap by offering financial services to underserved populations. These institutions use innovative lending mechanisms, such as group lending and social monitoring (Uddin et al., 2022), to reduce information asymmetry (Galarotis et al., 2011) and mitigate risks like moral hazard (Zeller, 1998). Through these models, MFIs create social pressure within lending groups that serves to reduce the risk of default.

Furthermore, the reliance on externally donated funds to provide loans and support projects aimed at poverty reduction and financial inclusion distinguishes MFIs from traditional financial intermediaries. While the financial intermediation role of MFIs is clear, the theory of agency problems provides an additional means of understanding the challenges faced by MFIs, specially in terms of the nature of financing sources. In traditional principal-agent relationships, the principal actively monitors the agent to ensure alignment of their interests. However, in the case of MFIs, the monitoring of managers by donors is often weak or nonexistent. Donors typically lack the resources or mechanisms to oversee how their funds are utilized, resulting in a situation where MFI managers have significant discretion over resource allocation. MFIs may claim to target the poorest segments, but the allocation of funds might prioritize operational sustainability or expanding outreach to relatively better-off clients who pose lower credit risks. This information gap can lead to mission drift, where MFIs, intentionally or unintentionally, deviate from their social objectives (Mersland & Strøm, 2010). This discretion can lead to suboptimal decision-making, such as prioritizing short-term expansion over long-term sustainability or engaging in practices that increase operational risks. Without adequate oversight, these decisions may lead to inefficiencies or practices that increase operational risks (Afrifa et al., 2019). MFI managers, enjoying a degree of autonomy over the utilization of funds, may prioritize short-term objectives, such as rapid expansion or increasing the scale of operations, over long-term sustainability.

This may lead to decisions that heighten operational risks or increase financial leverage, ultimately compromising the MFI's stability (Zeller, 1998). For example, the pursuit of growth funded by donations can lead to rising fixed operational costs, increasing the business risk for the MFI, through higher operating leverage (Chen, 2015). Without proper monitoring, the effectiveness of donations in achieving long-term sustainability remains uncertain. This misalignment of interests between donors and MFI managers creates an environment ripe for moral hazard, where managers may take on excessive risks without bearing the full consequences of those actions (Jensen & Meckling, 1979). Moral hazards arise when MFI managers are not held fully accountable for using donated funds, which can lead to inefficiencies in allocating these resources. The absence of strong regulatory oversight further compounds the problem of ensuring that funds are used efficiently and in line with financial inclusion objectives (Mersland & Strøm, 2010). On the contrary, if donors impose restrictions that prioritize specific outcomes over the overall sustainability of the institution (Hudon & Traca, 2011), the reliance on donations to fund MFI operations introduces an additional layer of complexity.

Thus, while MFIs play a critical role in promoting financial inclusion, their reliance on donations introduces significant challenges. The integration of agency theory with the concepts of financial intermediation, information asymmetry, and moral hazard provides a comprehensive framework for understanding the complexities of MFI operations and the challenges they face in maintaining financial stability and fulfilling their mission of poverty alleviation. To ensure the sustainability of MFIs and their ability to meet long-term financial inclusion goals, it is essential to address these issues, aligning the incentives of MFI managers with the objectives of donors and other stakeholders.

2.2. Conceptual analysis

In line with the focus of this study, in this section, we conceptually argue that the mechanism through which donations are transformed into financial services (i.e., loans) fundamentally shapes MFIs' operational structure and their long-term sustainability as financial institutions. This transformation process is central to understanding the unique challenges MFIs face in balancing their financial stability with their social objectives. MFIs' reliance on donation funding as opposed to deposit-based funds (Minton & Schrand, 1999; Armendáriz & Labie, 2011) shifts the conventional financial intermediation model into a socially motivated financial transfer system. In this system, donations represent the transfer of funds from surplus units – individual donors, philanthropic entities, and development organizations – to deficit units, particularly marginalized borrowers who are underserved by traditional financial institutions, typically through intervention of governments and non-governmental organizations (NGOs). The significance of donations to MFIs is rooted in their historical origins. Many MFIs began as NGOs (Serrano-Cinca & Gutiérrez-Nieto, 2014) and, as such, were important recipients of financial allocations in the form of donations. This legacy continues to shape the funding structures and operational practices of MFIs today.

MFIs receive funds through donations from development agencies,⁴ including the Department for International Development – DID (UK), DGIS (the Netherlands), CIDA (Canada), NOVIB (the Netherlands), NORAD (Norway), USAID, CGAP, and benevolent individuals. One can argue whether donations should be considered gifts from donors. However, donations are made to more significant causes to ensure the sustainability of society. For instance, one of the leading facilitators of donors' funds, Kiva,⁵ uses MFIs as financial intermediaries in selecting micro-borrowers and granting loans (Dorfleitner et al., 2020). However, the MFIs do not pay interest to

⁴ NOVIB: <https://www.oxfamnovib.nl/>; NORAD: <https://www.norad.no/en/front/>; USAID: <https://www.usaid.gov/>; CGAP: <https://www.cgap.org/>; DID: <https://tinyurl.com/2p88d4bd>; CIDA: <https://tinyurl.com/bdx7n7fb>.

⁵ Kiva, a donation-based NGO, is an online crowdlending platform that facilitates micro-borrowing by connecting socially oriented investors with the poor, aiming to support their small businesses (Dorfleitner et al., 2020).

Kiva's investors. Therefore, from a financial intermediation perspective, MFIs serve as conduits for channeling donor funds to borrowers, unlike banks that mobilize deposits and offer loans with the expectation of financial returns.

Accordingly, as a surplus entity in the economy, by sacrificing personal consumption and profit-seeking investment, donors engage in philanthropic acts as part of socially responsible investment (Renneboog et al., 2008) to improve the living conditions and economic opportunities of low-income people, to create a greater social impact by enhancing access to finance (Afrifa et al., 2019; Strøm et al., 2014). In addition, some donors enjoy tax benefits for transmitting their savings as donations to lend through MFIs,⁶ even though they do not seek any return from funds invested. Under this scenario, donors' funds have a greater cause to transfer to the MFIs for lending, making donations different from mere gifts. However, such cost-free donations do not pass on to recipients (micro-borrowers) free from cost.

The process of converting donations into loans introduces structural and operational complexities that warrant closer examination. Although this lending is often supported as a means of greater outreach to people with low incomes (Chakravarty & Pylypiv, 2015), the structural caveat of MFIs raises concerns from an institutional perspective. As financial intermediaries, MFIs face the challenge of deploying donated funds in a way that ensures both outreach and sustainability. While enabling MFIs to expand their lending operations, donations often contribute to operational inefficiencies when coupled with high fixed costs, such as administrative expenses and monitoring systems (Ledgerwood, 1998). Besides, the allocation of microloans from the donations is made at the discretion of MFI managers. While this discretion enables operational flexibility, it also increases the risk of misaligned priorities due to the lack of direct oversight from the donors.

Again, by nature, microfinance targets marginal borrowers who are considered unbankable by traditional banks because of their lack of collateral (de Aghion & Morduch, 2005). Since the credit risk profile of borrowers remains unchanged, MFIs use innovative lending methodologies, such as group lending and social monitoring, to reduce credit risk exposure from extending credit. In turn, they introduce a higher business risk exposure to their lending activities (Uddin et al., 2022), which arises from the greater operating costs of monitoring small and unsecured loans. In turn, the reliance on donations may reduce the pressure to optimize operational efficiency (Battilana & Dorado, 2010), as managers may assume that future funding will offset potential losses. This idea undermines the sustainability of the transformation mechanism, as donations intended to reduce borrowing costs for marginalized groups are often absorbed by operational expenses (Hudon & Traca, 2011; Tchuigoua, 2014).

Thus, moral hazard arises when MFI managers, operating with cost-free funds, are incentivized to engage in riskier or less efficient practices without fully bearing the consequences of failure. Consequently, this transformation mechanism further complicates the relationship between funding and sustainability. Rational understanding suggests that more donations are fundamentally linked to higher lending; however, given the inherent leverage in the MFI business model along with the potential agency and moral hazard problems, reliance on donation funding is likely to compromise the financial stability of MFIs and adversely affect their ability to survive.

2.3. Hypothesis development

Microfinance operations essentially reflect the fundamental mechanisms of financial intermediaries; however, they exhibit operational idiosyncrasies compared to traditional financial intermediaries. Unlike banks, MFIs have limited access to deposits and debts (Dorfleitner et al., 2017). Owing to such constraints, MFIs often consider deposit mobilization as an alternative source of funding (Gonzalez & Meyer, 2009). Instead, many of their credit operations rely on donations, grants, and subsidized equity in lending (Hudon & Traca, 2011; Minton & Schrand, 1999; Schaeck & Cihák, 2012). Despite ongoing formalization and commercialization to support financial sustainability, donations contribute significantly to MFI operations (Minton & Schrand, 1999; Schaeck & Cihák, 2012; Tchuigoua, 2016). Donation funding represents a unique aspect of the intermediation process in mobilizing savings (donations from savings) to marginal borrowers. However, donation dependency in these operations has consequences for the financial sustainability of MFIs (Al-Azzam, 2019).

When discussing financial sustainability or the soundness of MFIs, few studies address whether MFIs are vulnerable to market movements. Gonzalez (2010b) claims that MFIs have greater resilience for portfolios and credit growth during an economic slowdown because of their particular credit tools. Krauss and Walter (2009) find no statistically significant relationship between global market movements and MFIs. Hossain et al. (2020) report that financial stability in the MFI sector is moderately linked to the overall banking sector. A comparison of the drivers of MFI and bank solvency risk (Schulte & Winkler, 2019) demonstrates that MFI Z-scores are essentially the same as bank Z-scores. This finding implies that banks and MFIs share the same financial risk class and are driven by similar dynamics.

Academic interest in the stability of the microfinance sector has become prominent in the literature, particularly in the aftermath of the 2008 global financial crisis. Several studies have examined the vulnerability or resilience of the microfinance sector during this period of financial turmoil. In contrast to Krauss and Walter (2009), Di Bella (2011) reports that the performance of MFIs is significantly correlated with domestic and international financial conditions by examining their systematic risk during the crisis years (i.e., 2008 and 2009). Wagner and Winkler (2013) demonstrate that MFIs became vulnerable to financial turmoil, establishing that the credit growth of MFIs fell sharply during the crisis. Wagner (2012) contends that MFIs have lost their exclusive characteristics of

⁶ Kiva collects donors' funds using Donor-Advised Fund (DAF) mechanism, which gives Kiva access to new loan capital from individuals, foundations and corporations, while allowing those partners to receive an upfront tax deduction when they transfer funds to Kiva for lending (Retrieved from: <https://www.kiva.org/blog/updated-terms-of-use>).

greater resiliency during a crisis. The study observes that MFIs were affected similarly to traditional banks in the post-Lehman period. Although the number of studies is small, they provide an overview of the connections between the microfinance sector, financial markets, and other financial institutions. However, essential institutional aspects, including the financial stability of MFIs, are significantly missing from these findings.

To continue as effective financial intermediaries in the market, the financial stability of MFIs is critical, as they must cover the cost of lending money with the revenue generated from the outstanding loan portfolio, limiting these overheads as much as possible (Hermes et al., 2011). However, MFIs continue to rely on donation funding to maintain operations. Schulte and Winkler (2019) contend that MFIs are characteristically similar to banks, ignoring their unique donation funding model, which can have a substantially different effect on the risk-return scenario of microfinance operations, distinguishing them from mainstream lenders. Arguably, donations are uncertain funds that they cannot rely on to finance their operations. The unpredictable nature of donations intensifies the financial risks associated with operating leverage.

Moreover, the probability of generating funds through donations is disproportionately distributed among MFIs because of their relative size, with larger MFIs likely to have a greater reach in securing such funds because of their superior connectedness to donors. However, irrespective of the extent of reach to the donors, the reliance on donations adds a layer of complexity to MFI operations, particularly because it introduces governance-related challenges. As donations are cost-free funds, donors typically lack the mechanisms to monitor or evaluate the utilization of their donated funds rigorously. The moral hazard associated with cost-free donations compounds these challenges. MFI managers may inadvertently adopt riskier operational strategies, assuming that future donor contributions will mitigate any financial deficits. Such behavior can result in resource misallocation or the pursuit of overly ambitious expansion goals, further straining the financial resilience of the institution (Jensen and Meckling, 1979). These intertwined dynamics suggest that, while donations facilitate outreach, they may also undermine the financial stability of MFIs. Based on this reasoning, we postulate the following hypothesis:

H₁: Donations adversely affect the financial stability of MFIs.

Along with financial stability, the survival of financial institutions is a closely connected issue. Institutions with weakened financial stability are more likely to default on their obligations, especially in high-cost operational models such as microfinance (Berger et al., 2016). Since donation funding can engender instability in MFIs, it can also affect survival. In the case of MFIs, heightened operational costs combined with volatile donation funding may exacerbate the risk of institutional failure. Cost minimization is critical for enhancing the probability of survival of financial institutions such as cooperative banks (Fiordelisi & Mare, 2013). While donations provide the resources necessary for outreach, the resulting operational inefficiencies and governance challenges increase the probability of failure for institutions unable to manage their cost structures effectively. To substantiate this contention, we hypothesize the impact of donations on MFI survival as follows:

H₂: Increases in donations increase the probability of MFI failure.

3. Variables and test models

3.1. Dependent variables

In this study, we examine whether donations received by MFIs affect their financial stability and survival. We use the log of the Z-score (henceforth, Z-score) as a stability proxy that captures the variability of MFIs' net earnings and capital buffers (Beck et al., 2013, 2016; Demirgüç-Kunt & Huizinga, 2010; Schulte & Winkler, 2019; Uddin et al., 2020). This proxy is appropriate in the context of our investigation because we argue that MFIs become more financially unstable with greater lending through funding obtained from donations. The Z-score is calculated as:

$$Z - score = \frac{ROA + \frac{Equity}{Assets}}{\sigma ROA}$$

The ratio explicitly compares the risk buffers, such as return on assets (ROA) and the capital ratio (equity to assets) of a financial institution (i.e., an MFI) with the volatility of asset returns (Schulte & Winkler, 2019; Uddin et al., 2020). A higher Z-score indicates a lower probability of insolvency, or an MFI with greater financial stability.

Again, for the survival analysis, we follow two alternative approaches to represent MFIs' survival. In the first approach, we adopt a binary classification to capture MFI non-survival (failure), where the dummy variable equals 1 if an MFI failed and 0 otherwise. We construct this classification in three structured steps to ensure consistency in identifying survived and failed MFIs.

First, we identify MFIs that can be confidently categorized as having "survived." Specifically, we define MFIs as survivors (dummy = 0) if they report total asset data – the most consistently available indicator – for each year from 1999 to 2018. This 20-year period represents the full observation window of our dataset. MFIs that meet this condition are assumed to have been continuously operational throughout the sample period and thus classified as "survived."

Second, we examine the remaining MFIs, those that do not meet the 20-year reporting condition, and group them into three categories based on the start and end years of their data – Group A: MFIs that began reporting in or before 1999 but whose data end before 2018. Because their accurate start dates may precede the dataset's coverage, we cannot verify whether they operated for 20 years or not. Group B: MFIs that began reporting after 1999 and continue reporting through 2018. Their eventual survival beyond 20 years cannot be determined from our current dataset, Group C: MFIs that began reporting after 1999 and ceased reporting before 2018. These institutions can be clearly identified as operating for fewer than 20 years.

Third, we exclude Groups A and B from the analysis to avoid ambiguity in classifying institutions whose total operational period is uncertain. We retain only Group C, which we confidently define as failed MFIs (dummy = 1). This ensures that the survival vs. failure classification rests on verifiable data within the 1999–2018 period and avoids misclassification due to incomplete time series.

To further validate this classification, we report several real-world MFI liquidations during the sample period as evidence (see [Appendix G](#)). Based on public records, partner databases, and industry reports, we identified multiple MFIs across Africa, Asia, and Latin America that ceased operations during the sample period, often citing weak financial sustainability or high donation dependence. For instance, Vittana (USA, 2014), Trident Microfinance (India, 2014), and Energy in Common (USA, 2013) publicly documented their closure due to unsustainable models or overreliance on external funding. These cases, along with others listed in [Appendix G](#), indicate that non-reporting in Microfinance Information Exchange (MIX) frequently aligns with genuine institutional exit – while imperfect – can reasonably serve as a proxy for failure in this study. We also examine whether the excluded MFIs differ systematically from those classified as survivors and find patterns consistent with our main results.

In the second approach, we consider the “survival periods” (i.e., total years of operations of an MFI since its inception) as our dependent variable for survival analysis to complement the probabilistic analysis.

3.2. Independent variable

We use the donated equity amount (US\$) as our independent variable to represent the donations. To deal with the possibility that donation amounts may vary based on their size (i.e., total assets), we scale donated equity with the total assets (US\$) of MFIs. This allows us to standardize the variable by removing the scale or size effects of the MFIs, ensuring normality ([Laeven & Levine, 2009](#); [Grunert & Weber, 2009](#)). Hence, we define the focus independent variable as the log of the donated equity to total assets ratio (henceforth, Donations).

3.3. Institutional-level control variables

Following the literature, we select (i) equity-assets ratio, (ii) interest margin, (iii) cost ratio, and (iv) NPL ratio to control for MFI-level variations in our models. The equity-assets ratio is the ratio of an MFI's total equity to its assets. The effect of this ratio on the stability of financial institutions is well-established in the literature ([Schulte & Winkler, 2019](#)). A higher equity-assets ratio implies that equity holders bear more financial risk, which in turn strengthens their incentive to monitor managerial decisions. This enhanced discipline can improve borrower screening and credit monitoring practices, thereby increasing institutional soundness ([Coval & Thakor, 2005](#)). Equity is also associated with a reduction in financial institutions' systemic risk ([Anginer et al., 2018](#)). The interest margin represents the interest spread (interest income on loans – interest expenses on deposits) to total interest-earning assets, which determines a financial institution's ability to manage interest rate risk to control its profitability ([Angbazo, 1997](#); [Chaudron, 2018](#); [Nguyen, 2012](#)). Cost ratio is the ratio of operating expenses to the total loan portfolio, which determines the level of bank efficiency and influences stability ([Schaeck & Cihák, 2014](#)). Finally, the NPL ratio represents the percentage of non-performing loans in the total loan portfolio of MFIs. NPL ratio controls the effects of loan quality on the financial stability of financial institutions ([Beck et al., 2013](#); [Berger & DeYoung, 1997](#); [Uddin et al., 2020](#)). Financial institutions facing a high level of non-performing loans may increase the monitoring and screening costs of administering their existing loan portfolio and selling off problematic loans. Therefore, an increase in the NPL ratio can negatively affect the financial stability of financial institutions ([Berger & DeYoung, 1997](#); [Podpiera & Weill, 2008](#)).

3.4. Country-level control variables

As our sample includes global data, we control for country-level variations by identifying a set of macro-level control variables relevant to this study. These include annual growth in gross domestic product per capita (GDPPC) and inflation. We select GDPPC to control for the influence of monetary policy on financial institutions' financial stability ([Hauner & Peiris, 2008](#); [Uddin et al., 2020](#)). We include GDPPC to capture country-specific macroeconomic demand conditions that may influence microfinance institutions' financial outcomes and stability. Rather than serving as a direct proxy for monetary policy, GDPPC reflects the broader economic environment and income level in which MFIs operate. This approach is consistent with prior studies of financial institutions where GDPPC accounts for variation in aggregate demand conditions across countries (e.g., [Cull et al., 2011](#)). In addition, GDPPC factors in the local economic environment in which the MFIs operate are likely to influence the survival of financial institutions ([Fiordelisi & Mare, 2013](#); [Mare, 2015](#)). Conversely, we measure inflation with the annual percentage change in the consumer price index. We control for the effect of inflation because it serves as a proxy for macro-economic risk ([Fang et al., 2014](#)) and affects lending activities and the stability of financial institutions in the country in which it operates ([Boyd et al., 2001](#); [Hauner & Peiris, 2008](#); [Schulte & Winkler, 2019](#); [Uddin et al., 2020](#)).

3.5. Fixed effect control variable

Using multi-country data from 20 years, we apply a country-year interaction (Country*Year) variable. This variable captures the effects of unobservable country-level unknown factors on financial institutions' functions in a particular year in the country in which they operate. Previous studies have also used this interaction variable ([Beck et al., 2013](#); [Uddin et al., 2020](#)). We apply this variable to an OLS estimation.

3.6. Test models and estimations

We specify the following base model for the empirical test:

$$Z - score_{it} = \alpha_i + \beta_1 Donations_{it} + \sum_{k=1}^N \gamma_k Controls_{it} + \varepsilon_{it} \quad (1)$$

where $Z - score_{it}$ is the natural log of the Z-score of MFI i in year t . $Donations_{it}$ is the natural log of the donation to asset ratio received by an MFI i in year t . $Controls_{it}$ include both MFI-level controls (e.g., size, debt ratio, cost to asset, etc.) and country-level macroeconomic variables (e.g., inflation, GDP per capita), as well as country-year interaction terms to absorb unobserved country-specific time shocks. The summary of all test variables is available in [Appendix E](#). We estimate this base model in three ways. First, we estimate the OLS models after correcting the standard errors for country and year clustering. Second, we run an FE panel regression model, which corrects for time-invariant omitted variable bias across MFIs by demeaning individual heterogeneity.

$$Z - score_{it} = \alpha_i + \beta_1 Donations_{it} + \sum_{k=1}^N \gamma_k Controls_{it} + \mu_i + \varepsilon_{it} \quad (2)$$

Here, μ_i captures unobserved, time-invariant heterogeneity across MFIs, such as governance structure, institutional mission, or regional focus, that could bias the estimated coefficients if omitted. To validate the use of FE over a random effects (RE) specification, we conducted a Hausman test, which strongly supports the FE model ($\chi^2 = [\text{value}]$, $p < [\text{value}]$).

Third, we test the dynamic system GMM estimator proposed by [Blundell & Bond \(1998\)](#) to deal with endogeneity issues employing appropriate internal instruments. Specifically, we estimate the following dynamic model:

$$Z - score_{it} = \alpha_i + \beta_0 Z - score_{it-1} + \beta_1 Donations_{it} + \sum_{k=1}^N \gamma_k Controls_{it} + \varepsilon_{it} \quad (3)$$

In this framework, $Z - score_{it-1}$ is treated as an endogenous variable, while MFI-level controls are treated as weakly exogenous, and macroeconomic variables (GDP per capita and inflation) are considered exogenous. We use standard lagged levels and differences as internal instruments. We report the Hansen J-test results to assess instrument validity and the Arellano-Bond test for AR(2) to confirm the absence of second-order serial correlation. Overall, we can draw a strong inference about our hypothesis if the findings of the base model are consistent across all estimation approaches.

4. Data and sample

We collect data from the MIX.⁷ We consider an MFI to be included in our sample when it contains data on donations, which is the key focus of our study. We derive a global sample of 2,653 MFIs from 119 countries covering 1999 to 2018 by applying this sampling criterion. Our dataset comprises an unbalanced panel of MFIs, reflecting the varying durations and reporting frequencies inherent in the sector. This structure offers several advantages: First, it mitigates survivor bias by including institutions that may have ceased operations or reporting during the study period. [Shim \(2019\)](#) observes that utilizing unbalanced panel data in banking research helps avoid survivor bias and maximizes observational data. Second, it allows for the inclusion of all available data, enhancing the robustness and representativeness of our analysis. Third, it captures the dynamic nature of the microfinance industry, characterized by frequent institutional changes. By accommodating these real-world dynamics, our unbalanced panel approach provides a more accurate and comprehensive understanding of MFI stability and performance.

Overall, the sample MFIs come from a pool of countries in different regions. Notably, the dataset includes sample MFIs from Africa, East Asia and the Pacific, Eastern Europe and Central Asia, Latin America and the Caribbean, the Middle East and North Africa, and South Asia, as categorized by MIX. Among the countries from which the samples are drawn, India constitutes the most significant proportion, with 227 MFIs (8.56 % of the total sample), followed by 122 MFIs from Russia (4.6 %) and 116 MFIs from the Philippines (4.37 %). Several countries from different regions contribute to only one MFI in the sample: Belize, Bhutan, Fiji, Gabon, Saint Lucia, Samoa, Slovakia, Solomon Islands, Swaziland, Tonga, and Tunisia. Since MFIs operate largely in emerging markets, our study sample is globally representative. This enables us to draw inferences about the impact of donations on the financial stability of MFIs. The details of the sample distributions are presented in [Table 1](#).

We use the full sample presented in [Table 1](#) for the stability analysis. For the survival analysis, we develop a marginally reduced experimental sample dataset with a total sample of 2623 MFIs.⁸ According to the variable definition provided in [Section 3.1](#), only 77 MFIs fall under the survived group, remaining in operation for 20 years, from 1999 to 2018. The failed group of MFIs that commenced operations after 1999 and dissolved before 2018 comprises 2453 MFIs. The remaining 93 MFIs fall into either Group A or B, as defined

⁷ MIX Market is a data hub of the World Bank where microfinance institutions (MFIs) and supporting organizations share institutional data to broaden transparency and market insight about microfinance globally.

⁸ We remove 30 MFIs from the original sample. We remove only those MFIs that do not report their total assets data as we consider it the base for the calculation of survival periods as described in [Section 3.1](#).

Table 1
Sample Distributions.

Sl.	Country	No. of MFI	Sl.	Country	No. of MFI	Sl.	Country	No. of MFI	Sl.	Country	No. of MFI	Sl.	Country	No. of MFI
1	Afghanistan	18	25	Comoros	2	49	Hungary	1	73	Myanmar	15	97	South Africa	16
2	Albania	7	26	Congo, DPR	26	50	India	227	74	Namibia	2	98	Sri Lanka	27
3	Angola	2	27	Congo, Republic	5	51	Indonesia	68	75	Nepal	47	99	Sudan	2
4	Argentina	18	28	Costa Rica	17	52	Iraq	12	76	Nicaragua	37	100	Suriname	3
5	Armenia	16	29	Cote d'Ivoire	26	53	Jamaica	7	77	Niger	18	101	Swaziland	1
6	Azerbaijan	33	30	Croatia	2	54	Jordan	9	78	Nigeria	34	102	Syria	3
7	Bangladesh	84	31	Dominican Republic	18	55	Kazakhstan	35	79	Pakistan	52	103	Tajikistan	47
8	Belarus	3	32	East Timor	3	56	Kenya	33	80	Palestine	8	104	Tanzania	18
9	Belize	1	33	Ecuador	74	57	Kosovo	12	81	Panama	7	105	Thailand	3
10	Benin	34	34	Egypt	15	58	Kyrgyzstan	46	82	Papua New Guinea	9	106	Togo	30
11	Bhutan	1	35	El Salvador	20	59	Laos	30	83	Paraguay	7	107	Tonga	1
12	Bolivia	28	36	Ethiopia	22	60	Lebanon	6	84	Peru	73	108	Trinidad & Tobago	3
13	Bosnia & Herzegovina	17	37	Fiji	1	61	Liberia	4	85	Philippines	116	109	Tunisia	1
14	Brazil	47	38	Gabon	1	62	Macedonia	4	86	Poland	4	110	Turkey	2
15	Bulgaria	25	39	Gambia	3	63	Madagascar	17	87	Romania	7	111	Uganda	34
16	Burkina Faso	30	40	Georgia	20	64	Malawi	10	88	Russia	122	112	Ukraine	3
17	Burundi	22	41	Ghana	70	65	Malaysia	1	89	Rwanda	44	113	Uruguay	2
18	Cambodia	21	42	Grenada	2	66	Mali	22	90	Saint Lucia	1	114	Uzbekistan	35
19	Cameroon	30	43	Guatemala	26	67	Mexico	107	91	Samoa	1	115	Venezuela	2
20	Central African Republic	2	44	Guinea	8	68	Moldova	10	92	Senegal	79	116	Vietnam	43
21	Chad	4	45	Guinea-Bissau	4	69	Mongolia	10	93	Serbia	4	117	Yemen	9
22	Chile	6	46	Guyana	1	70	Montenegro	4	94	Sierra Leone	11	118	Zambia	10
23	China	59	47	Haiti	8	71	Morocco	10	95	Slovakia	1	119	Zimbabwe	8
24	Colombia	44	48	Honduras	28	72	Mozambique	11	96	Solomon Islands	1		Total	2653

The sample comprises MFIs from Africa, East Asia & Pacific, East Europe & Central Asia, Latin America & Caribbean, MENA, and South Asia. The data of MFIs are collected from the Microfinance Information Exchange (MIX) database.

in Section 3.1. Sample segregation indicates that most MFIs could not survive for at least 20 years after starting operations. In Section 5.6, we empirically explore whether donations significantly affect failure or non-survival.

Table 2 presents the Summary Statistics and Correlation Analysis results. In Panel A of Table 2, the descriptive statistics show the means, standard deviations, and minimum and maximum values of each variable. Our variables (those not taken in logged values) are winsorized at the 5 % threshold to minimize the outlier effects at the upper and lower tails of the distribution and ensure consistent estimations in subsequent analyses to address potential distortions from extreme values, following standard practice in the banking and finance literature (Ioannidou et al., 2015). Although we employ the logged values of Z-scores and the Donations in our regression analyses, we present the original, unlogged values in Table 2 for interpretability. We find that the dependent variable Z-score varies within a non-zero positive range from 0.251 to 151.973, with an average value of 32.322 and a standard deviation of 38.626. The independent variable, Donations, ranges from 0 to 8.958. The maximum observed value of 8.958 reflects outlier cases in which donations were disproportionately high relative to the institution's asset base in a given year.

Among the MFI-level variables, the NPL ratio shows a lower variation, with a standard deviation of 0.013. In addition, the NPL ratio shows that MFIs have relatively fewer problem loans, with an average of 1.1 %. However, the difference between the minimum and maximum values of the interest margin variables demonstrates the variations in the interest margins charged by the MFIs. Notably, the interest rate margin between the loan portfolios and deposits is as high as 58.3 %. Moreover, the equity asset ratio shows that MFIs hold an average of 33.9 % of equity against their assets. However, the equity holdings of MFIs raise concerns about a lower minimum value (0.03) and a high standard deviation value (0.257). The cost ratio shows that MFIs have an average operating cost of 25.1 %, which is as high as 74.8 %, with a standard deviation of 0.186. Among the country-level variables, inflation shows higher values than GDPPC for all parameters. Finally, variations in the number of observations are considerably high, mainly owing to the availability of a small amount of MFI-level data compared with country-level data.

In addition to the descriptive statistics, we examine the correlation matrix among the variables, presented in Panel B of Table 2. The results indicate that the pairwise correlations among the explanatory variables are generally low to moderate, with no correlation coefficient exceeding the conventional threshold of 0.70, suggesting no immediate concern of multicollinearity (Dormann et al., 2013). We further conduct the Variance Inflation Factor (VIF) test to assess multicollinearity more formally. The VIF values for all explanatory variables are well below the commonly accepted benchmark of 10 (mean VIF = 1.371), reinforcing the conclusion that multicollinearity is unlikely to bias our regression estimates (Gujarati & Porter, 2009; Greene, 2018). We do not report the VIF results Table to maintain the brevity of the manuscript. Hence, we proceed with the regression analysis with confidence in the reliability of our control variable set.

Table 2
Summary Statistics and Correlations.

Panel A: Descriptive Statistics								
Variable	Observations	Mean	SD	Min	Max			
Z-score	12,131	32.297	38.515	0.279	151.229			
Donations	11,300	0.103	0.253	0	8.958			
Equity-assets ratio	18,452	0.339	0.257	0.03	0.921			
Interest margin	12,413	0.242	0.14	0.057	0.583			
Cost ratio	15,057	0.251	0.186	0.059	0.748			
NPL ratio	11,851	0.011	0.013	0	0.049			
GDPPC	52,721	3.348	3.837	−47.591	49.48			
Inflation	48,600	7.857	19.664	−18.109	513.907			
Panel B: Correlation Matrix								
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Z-score	1.000							
(2) Donations	−0.018	1.000						
(3) Equity-assets ratio	0.217	0.378	1.000					
(4) Interest margin	−0.154	0.110	0.255	1.000				
(5) Cost ratio	−0.237	0.234	0.214	0.695	1.000			
(6) NPL ratio	−0.096	0.057	0.038	0.123	0.178	1.000		
(7) GDPPC	−0.026	0.058	0.015	−0.040	−0.000	−0.006	1.000	
(8) Inflation	−0.016	0.053	0.021	0.008	0.026	−0.012	−0.014	1.000

Panel A presents the summary statistics of the study variables, including the sample size (Observations), average value (Mean), standard deviation from the mean (SD), as well as the lower (Min) and upper (Max) limits of data for each variable. Z-score is the proxy for the stability of financial institutions, which is calculated as $(ROA + \text{Equity-asset ratio})/\sigma ROA$; Donations is the ratio of donated equity to total assets received by an MFI; Equity-assets ratio is the ratio of an MFI's total equity to total assets; Interest margin represents the ratio of interest margin (interest income on loans – interest expense on deposits) to total interest-earning assets; Cost ratio is the ratio of operating expense to total loan portfolio; NPL ratio is the ratio of non-performing loans in the total loan portfolio of an MFI; GDPPC is the annual growth in gross domestic product per capita; Inflation is the annual rate of inflation of a country. The variables (those not taken in logged values) are winsorized at 5 % threshold to minimize the outlier effects at the upper and lower tails of the distribution and ensure consistent estimations in analyses to address potential distortions from extreme values. Panel B shows the pairwise correlation among the study variables. A correlation coefficient < 0.70 suggests immediate concern of multicollinearity (Dormann et al., 2013).

5. Results and discussions

5.1. Baseline estimation results

In Table 3, we present the results of our baseline model with three econometric estimations: OLS, FE, and GMM. The relationship between Donations and Z-score is negative and statistically significant for the baseline OLS estimates. In the OLS estimation, the association is significant at the 1 % level. We find that a 1 % increase in the Donations negatively affects the Z-score of MFIs by 0.10 %. While this impact may appear modest in magnitude, the practical implication is meaningful, since even a small decline in the Z-score reflects a reduction in the MFI's buffer against insolvency risk. The Z-score combines profitability, leverage, and earnings volatility, and a lower score indicates that an institution is closer to breaching its risk threshold. Thus, despite being cost-free, higher reliance on donation-based funding may expose MFIs to greater instability due to associated operating leverage and earnings uncertainty.

We further check the robustness of the OLS estimation results by re-estimating the test model using the FE and GMM estimators. The relationship remains significant at the 1 % level in the FE estimator, with an estimated coefficient of -0.07 . The estimated coefficient of GMM is somewhat higher at $\hat{\beta} = -0.29$. However, in this case, the relationship between Donations and Z-score is significant only at the 10 % level. With subtle differences, the relationship between the independent and dependent variables remains consistently negative and significant across the estimators. Hence, we establish that our estimations are not sensitive to estimation technique bias and find a reliably negative association between the variables of interest. Accordingly, we provide sufficient empirical evidence to support our first hypothesis (H_1 : Donations adversely affect the financial stability of MFIs).

5.2. Sub-sample analysis

After drawing inferences from the baseline estimations on the global dataset, we investigate the relationship using several sub-sample analyses. Specifically, we consider variations in the business orientation based on MFIs' legal status and profit orientations.

Table 3
Baseline Regression Results.

Variables	Z-score OLS	Fixed effect	GMM
Z-score _{t-1}	—	—	0.56*** (5.03)
Donations	-0.10^{***} (-8.45)	-0.07^{***} (-3.29)	-0.29^* (-1.82)
Equity-assets ratio	2.48^{***} (19.89)	2.36^{***} (10.04)	2.10 (0.92)
Interest margin	0.40 (1.61)	0.46 (1.16)	-1.84 (-0.39)
Cost ratio	-3.18^{***} (-13.83)	-2.96^{***} (-6.40)	-5.13 (-1.01)
NPL ratio	-9.94^{***} (-4.82)	-11.58^{***} (-4.26)	-15.74 (-0.29)
GDPPC	-0.02^{***} (-3.17)	-0.00 (-0.22)	0.00 (0.17)
Inflation	-0.01^* (-1.92)	-0.01 (-1.12)	0.00 (0.52)
Constant	2.63^{***} (24.35)	2.61^{***} (14.59)	1.32 (0.52)
Observations	3,397	3,397	2,821
Country & Year FE	Yes	N/A	N/A
R-squared	0.26	0.10	N/A
F value/Wald χ^2 value	95.25	22.50	94.49
Hausman Test	N/A	0.00	N/A
Modified Wald [p-value]	N/A	0.00	N/A
Wooldridge autocorrelation [p-value]	N/A	0.00	N/A
AR (1)	N/A	N/A	0.00
AR (2)	N/A	N/A	0.10
Hansen J	N/A	N/A	0.52
Number of instruments	N/A	N/A	21
Number of groups	N/A	882	742

We estimate $Z\text{-scores}_{it} = \alpha_i + \beta_1 \text{Donations}_{it} + \gamma \text{Controls}_{it} + \varepsilon_{it}$ by using OLS, FE, and a dynamic panel of system GMM estimators. We include $Z\text{-score}_{it-1}$ as a lag variable in the GMM model. $Z\text{-score}$ is the proxy for MFI stability, the score calculated as $(\text{ROA} + \text{capital-asset ratio})/\sigma\text{ROA}$, where ROA equals the ratio of net income to total assets. *Donations* is the log of donated equity to total assets received by an MFI. *Controls* are vectors of control variables defined in the Appendix. *Country & Year FE* is an interaction variable used in the OLS based on the literature. Still, it is not applied to the FE estimation and system GMM, as supporting literature is unavailable. The variable captures the effects of unobservable country-level unknown factors on MFIs' functions in a particular year that operates in a country. The values within parentheses are robust t-stats adjusted for heteroscedasticity. The asterisks ***, **, and * denote significance at less than 1 %, 5 %, and 10 % levels.

The rationale behind these categorizations stems from the fact that MFIs' reliance on donations depends on the profit orientation, as nonprofit MFIs rely more on donations (Goodell et al., 2020). Also, the profit orientation is commonly linked with the nature of the organization, with NGO MFIs being typically not-for-profit endeavors and reliant on donations for financing (Battilana and Dorado, 2010). The average donation in relation to assets is higher for NGO MFIs than for other MFIs. A higher average reliance on donations by not-for-profit MFIs than for-profit MFIs gives a preliminary analytical basis across these dimensions. Also, F-statistics from the ANOVA tests show significant variations among groups (See Panels A & B of Appendix C).⁹

Accordingly, Table 4 presents the first set of sub-sample analyses from the two dimensions. First, we consider that the effect of donations may vary owing to the profit orientation of the MFIs. The literature suggests that profit-seeking MFIs are less dependent on donations; instead, they focus on self-sustainability by generating profits (Chakravarty & Pylypiv, 2015). Therefore, their dependence on donations may vary, as may the effects of donations on their financial stability.

Table 4 shows that donations adversely affect the financial stability of MFIs, irrespective of their profit orientation. Interestingly, the adverse effect is somewhat more detrimental to non-profit MFIs ($\beta = -0.111$) than for-profit MFIs ($\beta = -0.085$). While this suggests that non-profit MFIs may be more sensitive to donation-induced instability, further insights arise when we consider legal ownership forms.

We also present relationship variations based on the legal status under which microfinancing activities are conducted. Based on the legal status of operations, the MIX market classifies them into six categories: NGOs, non-bank financial institutions, banks, rural banks, credit unions/co-operatives, and other MFIs. Again, the nature of their legal incorporation indicates their opportunity to secure donor funding and their dependence on it to varying degrees. Consequently, this sub-sample analysis aims to understand whether any particular type(s) of MFI benefits from donation financing, while others may have a more detrimental effect. We present the findings of our analysis of legal status-based variations in Table 5.

Table 5 shows that although NGOs tend to receive more donations on average (as shown in Appendix C), the estimated effect of donations on stability ($\beta = -0.087$) is less damaging than for bank-type MFIs (e.g., Bank MFI = -0.119 ; Rural Bank MFI = -0.204). This does not necessarily contradict our earlier findings, as the magnitude of the regression coefficient reflects both the volume of donations received and the sensitivity of that institutional form to donation-related volatility. While NGOs may absorb donor funds as part of their core operating model, more commercially structured institutions may exhibit stronger negative responses to even modest donation reliance, possibly due to misaligned incentives or disruptions to financial discipline. Accordingly, these findings underscore the importance of interpreting the donation–stability relationship not only through profit orientation or legal status in isolation, but through a more integrated lens that considers donation dependency and institutional adaptability. More importantly, the negative effect of donations on the financial stability of MFIs persists irrespective of organizational type or structure.

Besides analyzing the donations–financial stability relationship of MFIs in relation to various dimensions of their institutional characteristics, we further factor in possible variations based on the regions in which they operate. Since the regulatory environment differs in different locales, MFIs may regulate donation funding differently, or the flow of donations may vary due to other inherent regional characteristics such as political and economic instability or conflict. In addition, donations may be channeled differently in some countries because of the prevailing MFI outreach (Lapenu & Zeller, 2002). We further explore regional variation in donation dependency to better contextualize our sub-sample regression results. Panel C of Appendix Table C presents the mean donation-to-asset ratios by region, showing that MFIs in the Middle East and North Africa rely most heavily on donation funding (mean = 0.320), followed by Africa (0.125) and Eastern Europe and Central Asia (0.122). By contrast, Latin America and the Caribbean exhibit the lowest reliance (0.062). The differences across regions are statistically significant (ANOVA F-statistic = 110.37, $p < 0.01$), confirming the global heterogeneous nature of donation flows. This variation helps frame the region-specific effects of donations observed in our stability analysis. Therefore, analyzing the relationship between samples across different regional specifications allows us to gain a more holistic view. Table 6 presents the results of the sub-sample analysis.

In Table 6, we do not identify any discrepancies in the relationships between the variables of interest. The impact of donations has a consistently negative and statistically significant effect on the stability of the MFIs, except for those in Eastern Europe and Central Asia. The relationship for these regions remains negative but statistically insignificant. In contrast, MFIs operating in East Asia and the Pacific region are the most unstable, with higher donations used in their operations, signified by the highest regression coefficient value. Hence, our regional-level sub-sample analysis further corroborates our contention that donations have a negative impact on MFIs' financial stability.

5.3. Robustness check

Different econometric estimators are used to estimate the baseline model of the study and subsequent sub-sample analyses to provide a solid grounding to support the conclusions reached in the earlier sections regarding the negative impact of donations on MFIs' financial stability. This section presents a robustness check using pooled quantile regression (Koenker & Bassett, 1978) to test whether the relationship between donations and financial stability holds across different points of the conditional distribution of the Z-score. Unlike OLS, which focuses solely on the mean effect, quantile regression enables us to examine how the effect of donations varies across MFIs with different stability levels. This section confirms whether our estimates are consistent with the normality of the sample distribution. Quantile regression is a semi-parametric approach that does not require assumptions about the normality or

⁹ We also examine the pattern and persistence of donations over time by profit orientation, and find that non-profit MFIs consistently exhibit higher donor support, whereas for-profit MFIs show a lower reliance on donations.

Table 4
Donations-MFI Stability Relationship – Profit Orientation-based Variations.

Variables	Z-score
For-profit MFI	−0.085*** (−7.275)
Non-profit MFI	−0.111*** (−8.058)
Equity-assets ratio	2.461*** (20.165)
Interest margin	0.394 (1.585)
Cost ratio	−3.162*** (−13.726)
NPL ratio	−10.273*** (−4.934)
GDPPC	−0.018*** (−3.414)
Inflation	−0.008* (−1.877)
Constant	2.641*** (25.063)
Observations	3397
Country & Year FE	Yes
R-Squared	0.264
F value	86.81

We estimate $Z\text{-score}_{it} = \alpha + \beta_1 \text{Donations}_{it} * \text{MFI profit orientations dummy} + \gamma \text{Controls}_{it} + \varepsilon_{it}$, where we introduce two interaction terms between Log of donation to asset ratio and dummy variable for MFI profit orientation. We take the profit orientation status reported in the MIX market database to generate the dummy variables. *Country & Year FE* is an interaction variable used in the OLS based on the literature. The variable captures the effects of unobservable country-level unknown factors on MFIs' functions in a particular year that operates in a country. The values within parentheses are robust t-stats adjusted for heteroscedasticity. The asterisks ***, **, and * denote significance at less than 1 %, 5 %, and 10 % levels.

homoscedasticity of residuals (Koenker & Bassett, 1978). Given the cross-sectional variation in MFI characteristics and the potential for uneven impacts of donations, pooled quantile regression offers a broader perspective on the stability effects than mean-based models.

The median-based quantile regression technique has particular advantages over traditional mean-based OLS regression. The main advantage of this technique is that, unlike OLS, it is associated with the exemption of normal data distribution. Median regression fits a regression line through all observations by minimizing the sum of absolute errors, estimating the median of the conditional distribution (Klomp and de Haan, 2012). This allows us to infer the regression results by considering the entire distribution of the dependent variable (Coad & Rao, 2008; Jiang et al., 2020). In addition, quantile regression efficiently estimates relationships by reducing interference from outliers and heavy-tailed distributions (Canay, 2011). Thus, the quantile regression approach offers a more complete view of the effects of explanatory variables on dependent variables. Accordingly, we measure the relationship between the dependent and independent variables at the lower, median, and upper quantiles (i.e., q25, q50, and q75) of the dependent variable, and the results are presented in Table 7.

The results in Table 7 show that the coefficients of MFIs are negative and significant for all quantiles at the 1 % level. We observe a negative impact of Donations on the Z-score at each quantile of the Z-score distribution. In addition, we find that the regression coefficients do not vary substantially across quantiles. We detect a slight upward trend in the coefficients from the lower (25th quantile) to the median quantile (50th quantile). However, the coefficient decreases somewhat in the upper quantile (75th quantile) of the dependent variable. The quantile estimation results generally confirm the results of the mean-based baseline estimates. Notably, the coefficients across quantiles are close to the estimated coefficient of the OLS estimation ($\beta = -0.10$). Overall, our quantile estimation results confirm no tail dependence in the relationship between donation and MFI stability. Thus, the robustness test validates the inference drawn from our baseline estimation that donation funding adversely affects the stability of MFIs.

5.4. Endogeneity issue

A crucial consideration in drawing reliable conclusions from econometric estimations is the presence of potential endogeneity.

Table 5

Donations-MFI Stability Relationship – Legal Status-based Variations.

Variables	Z-score
NGO MFI	−0.087*** (−5.458)
NBFI MFI	−0.056*** (−4.370)
Bank MFI	−0.119*** (−9.764)
Rural Bank MFI	−0.204*** (−5.783)
Credit Union/Cooperative MFI	−0.151*** (−9.065)
Other MFI	−0.053 (−0.972)
Equity-assets ratio	2.480*** (20.436)
Interest margin	0.745*** (2.929)
Cost ratio	−3.278*** (−14.152)
NPL ratio	−11.127*** (−5.469)
GDPPC	−0.017*** (−3.396)
Inflation	−0.008* (−1.878)
Constant	2.608*** (24.361)
Number of Observations	3397
Country & Year FE	Yes
R-Squared	0.275
F value	62.66

We estimate $Z\text{-score}_{it} = \alpha + \beta_1 \text{donations} * \text{MFI legal status dummy} + \gamma \text{Controls}_{it} + \varepsilon_{it}$, where we introduce six interaction terms between Donations and dummy variable for MFI legal status. We take the legal status reported in the MIX market database to generate the dummy variables. *Country & Year FE* is an interaction variable used in the OLS based on the literature. The variable captures the effects of unobservable country-level unknown factors on MFIs' functions in a particular year that operates in a country. The values within parentheses are robust t-stats adjusted for heteroscedasticity. The asterisks ***, **, and * denote significance at less than 1 %, 5 %, and 10 % levels.

Endogeneity may arise from several sources, such as reverse causality, omitted variable bias, and measurement errors (Daher et al., 2015; Rahaman & Zaman, 2013). We consider the possibility of the influence of endogeneity, which may invalidate our statistical interpretations of our baseline OLS estimator. We re-estimate the study model using FE and GMM models to avoid such biases. The FE model reduces the endogeneity bias from omitted variable problems that may arise from unobservable time-invariant institutional characteristics and removes cross-sectional variation across financial institutions (Vallascas et al., 2017).

Again, endogeneity may arise from reverse causality; for instance, a more stable MFI may effectively draw donation funds into its operations. To mitigate this concern, we adopt a two-stage least squares (2SLS) estimation strategy, employing an instrumental variable approach that helps isolate the causal effect of donations on financial stability. Specifically, we use the log of borrowings (henceforth, Borrowing) as the instrument for donations. Our choice is theoretically grounded in the funding trade-off – MFIs capable of attracting commercial borrowings are typically less dependent on donations as a funding source (Hudon & Traca, 2011). Consistent with this expectation, our result reveals a negative relationship between donations and borrowings (see Panel A of Table 8).

In the first-stage regression in the same panel, Borrowing is significantly and negatively associated with donations, confirming instrument relevance. Additionally, Borrowing is excluded from the second-stage regression, satisfying the exclusion restriction. To reinforce our identification strategy, we report Durbin–Wu–Hausman and Anderson–Rubin test statistics (Panel B of Table 8). These diagnostics confirm the instrument's validity and indicate no evidence of weak instrumentation or remaining endogeneity.

Although borrowings may capture institutional characteristics such as risk appetite or market access, the evidence – supported by diagnostics and prior studies – suggests their direct impact on stability is limited compared to their substitution role. We further support our instrument choice by referencing recent empirical studies. Shettima and Dzolkarnaini (2024), using dynamic GMM, show that borrowings and deposits act as substitutes in MFIs, particularly where capital markets are more developed. This substitution relationship provides strong evidence that borrowings function as a replacement for other external funding sources, including

Table 6
Donations-MFI Stability Relationship – Regional Variations.

Variables	Z-score
Africa	−0.100*** (−6.066)
East Asia & Pacific	−0.180*** (−8.625)
East Europe & Central Asia	−0.026 (−1.145)
Latin America & Caribbean	−0.112*** (−8.213)
MENA	−0.106*** (−2.620)
South Asia	−0.039** (−2.137)
Equity-assets ratio	2.448*** (20.751)
Interest margin	0.334 (1.369)
Cost ratio	−3.267*** (−13.949)
NPL ratio	−10.570*** (−5.193)
GDPPC	−0.012** (−2.362)
Inflation	−0.008* (−1.911)
Constant	2.710*** (26.399)
Number of Observations	3397
Country & Year FE	Yes
R-Squared	0.279
F value	68.87

We estimate $Z\text{-score}_{it} = \alpha + \beta_i \text{Donations}_{it} * \text{regional dummy} + \gamma' \text{Controls}_{it} + \varepsilon_{it}$, where we introduce six interaction variables interacting between Donations and dummy variables for six different regions based on the regional categorization provided by the MIX Market database. *Country & Year FE* is an interaction variable used in the OLS based on the literature. The variable captures the effects of unobservable country-level unknown factors on MFIs' functions in a particular year that operates in a country. The values within parentheses are robust t-stats adjusted for heteroscedasticity. The asterisks ***, **, and * denote significance at less than 1 %, 5 %, and 10 % levels.

donations. In Table 8 (Panel B), the 2SLS regression results confirm that the relationship between donations and Z-scores remains negative, reinforcing our finding that heavy donor reliance undermines financial stability.

Furthermore, our GMM estimator (see Table 3) uses internal instruments to eliminate potential endogeneity (Beutler et al., 2020). In particular, we apply the two-step system-GMM technique (Blundell & Bond, 1998). The system-GMM procedure allows for the generation of appropriate instruments from within the models, providing orthogonality conditions between the lagged values of the dependent variable and disturbances (Arellano & Bond, 1991). The lagged variables correlate with their original variables, insulating explanatory variables from their error terms (Lee & Kim, 2020). The instruments generated in the GMM estimation are validated. The statistical insignificance of the Hansen test confirms that the conditions for over-identifying moments are valid. Moreover, the significance of the first-order autocorrelation AR (1) and the insignificance of the second-order autocorrelation AR (2) test confirm the lack of autocorrelation in the first-differenced errors. Furthermore, we verify the absence of instrument proliferation (Roodman, 2009) and follow Windmeijer corrected (WC-robust) standard errors in the two-step estimation, which allows us to produce variance-covariance estimates that are robust to heteroscedasticity (Daher et al., 2015).

The consistency in the findings of the FE and GMM estimators (Table 3) and the 2SLS estimation (Table 8) provides clear global evidence to support the reliability of our OLS estimation results. Hence, even when considering possible endogeneity bias, the empirical tests support the hypothesis that donation funding adversely affects MFI stability.

5.5. Sample selection

We collect our data from the MIX database to achieve the study objective of understanding the impact of donations on MFIs' stability. However, due to the lack of data availability and the nature of the study, collecting a random sample was impossible. This could lead to a sample selection bias, which may impact the estimations and generalizability of the findings. Hence, we address the

Table 7
Robustness Test – Quantile Regression.

Variables	Z-score 25th Quantile	50th Quantile	75th Quantile
Donations	−0.092*** (−9.038)	−0.097*** (−8.730)	−0.086*** (−6.532)
Equity-assets ratio	2.274*** (20.954)	2.329*** (21.416)	2.147*** (15.251)
Interest margin	0.464 (1.555)	0.119 (0.491)	−0.148 (−0.413)
Cost ratio	−3.055*** (−12.329)	−2.868*** (−12.663)	−2.625*** (−10.048)
NPL ratio	−10.843*** (−6.247)	−11.731*** (−5.808)	−10.675*** (−4.909)
GDPPC	−0.018*** (−3.828)	−0.015*** (−2.752)	−0.011 (−1.305)
Inflation	−0.008 (−1.540)	−0.010*** (−3.341)	−0.010** (−2.016)
Constant	2.088*** (20.987)	2.663*** (27.897)	3.421*** (27.226)
Observations	3,397	3,397	3,397
Country & Year FE	Yes	Yes	Yes
Pseudo R-squared	0.18	0.14	0.11

We estimate $Z\text{-score}_{it} = \alpha_i + \beta_i \text{Donations}_{it} + \gamma \text{Controls}_{it} + \varepsilon_{it}$ by using quantile regressions at 25th, 50th and 75th quantiles. *Z-score* is the proxy for MFI stability, the score calculated as $(\text{ROA} + \text{capital-asset ratio})/\sigma\text{ROA}$, where ROA equals the ratio of net income to total assets. *Donations* is the log of donated equity to total assets received by an MFI. *Controls* are vectors of control variables defined in the [Appendix](#). The values within parentheses are robust t-stats adjusted for heteroscedasticity. The asterisks ***, **, and * denote significance at less than 1 %, 5 %, and 10 % levels.

potential sample selection bias by employing Heckman's (Heckman, 1979) two-stage method. The Heckman correction method is a statistical technique for correcting bias in non-randomly selected samples (Karaca-Mandic and Train, 2003).

In the first stage, we employ a probit estimation to determine the probability of an MFI using donations as a source of funding in relation to their deposit funding. Accordingly, we construct a deposit dummy equal to 1 if the MFI's deposit-assets ratio exceeds 50 %. MFIs' reliance on donations considerably lowers their dependence on deposits, as evidenced by their asset-liability structure compared with other financial institutions, such as banks (Uddin et al., 2022). We estimate a probit model to predict whether an MFI is likely to rely on donation-based funding, using a deposit dummy as the dependent variable (equal to 1 if the deposit-to-asset ratio exceeds 50 %).

Following standard practice, our model comprises two equations: the Selection Equation (First Stage – Probit) and the Outcome Equation (Second Stage – OLS with IMR). Let, S^* be the latent variable indicating the propensity of an MFI to rely on donation-based funding in the first stage. $S = 1$ if $S^* > 0$, meaning the MFI is selected into the donation-reporting group.

$$S^* = \delta Z_i + \mu_i \quad (4)$$

$$S_i = 1 \text{ if } S_i^* > 0$$

Where, Z_i includes covariates such as the deposits-to-loans ratio (as an exclusion restriction), equity-asset ratio, cost ratio, and other institutional controls. μ_i is the error term.

The deposits-to-loans ratio and standard controls are used as an exclusion restriction. MFIs that use deposits as a sizeable funding source are more cost-effective in their businesses (Caudill et al., 2009), which may affect their financial stability. From this model, we compute the inverse Mills ratio (IMR), which captures the likelihood of selection into the donation-receiving group. In the second stage, we include the lagged IMR in the OLS regression to correct for potential selection bias in estimating the effect of donations on financial stability. The significant coefficient on the IMR confirms the presence of selection effects and supports the robustness of our baseline findings.

$$Y_i = \beta X_i + \lambda \widehat{IMR}_{i,t-1} + \varepsilon_i \quad (5)$$

Where, Y_i is the outcome variable (Z-score), X_i includes the main explanatory variable (i.e., Donations) and relevant controls, $\widehat{IMR}_{i,t-1}$ is the lagged Inverse Mills Ratio from the first-stage probit estimation, λ captures the selection bias correction, and ε_i is the error term.

As expected, [Table 9](#) shows that the deposits-to-loans ratio is significantly and positively related to the deposit dummy, indicating the validity of the exogenous variable. Following Mollah et al. (2021) and Uddin et al. (2023), we control for self-selection bias through the IMR and find that our primary results align with the baseline estimations (see [Table 3](#)). Thus, we argue that the results are less likely to be driven by self-selection bias.

Table 8
Endogeneity Test – 2SLS.

Panel A: First-stage regression result	
Variables	Donations
Borrowing	– 0.124*** (–5.15)
Equity-assets ratio	0.047*** (26.91)
Interest margin	–0.814* (–1.88)
Cost ratio	2.264*** (7.62)
NPL ratio	0.994 (0.34)
GDPPC	0.030*** (3.91)
Inflation	0.003 (0.47)
Constant	–3.770*** (–9.11)
Observations	3,044
Country & Year FE	Yes
R-squared	0.301
F value	163.76
Durbin–Wu–Hausman (p-value)	0.074
Anderson–Rubin (p-value)	0.000
Panel B: 2SLS regression results	
Variables	Z-score
Donations	–0.294*** (–2.64)
Equity-assets ratio	0.035*** (6.26)
Interest margin	0.198 (0.64)
Cost ratio	–2.550*** (–5.79)
NPL ratio	–11.082*** (–5.40)
GDPPC	–0.011* (–1.69)
Inflation	–0.009** (–2.33)
Constant	1.490** (2.25)
Observations	3,044
Country & Year FE	Yes
R-squared	0.178
F value	93.82

In Panel A, Borrowing is the log value of total borrowings by the MFIs. We also confirm the endogeneity and weak instrument validity for the model. The Durbin–Wu–Hausman test ($p = 0.073$) examines the endogeneity of the potentially endogenous regressor (Donations), where a significant p-value suggests rejection of the exogeneity null. The Anderson–Rubin test ($p = 0.003$) assesses the joint significance of the instruments in the structural equation, providing a robust test even in the presence of weak instruments. Panel B presents the second-stage regression results. The values within parentheses are robust t-stats adjusted for heteroscedasticity. The asterisks ***, **, and * denote significance at less than 1 %, 5 %, and 10 % levels.

5.6. MFI survival analysis

To provide empirical evidence in support of the second hypothesis of our study (H_2 : Donations increase the probability of MFI non-survival), we test non-survival probability using alternative probabilistic models. We then show the direct impact of donations on the MFI survival period and the influence of financial stability using OLS regression, and how this is transmitted through the instability of MFIs.

Using probit regression, we first test whether donations increase the probability of failure or non-survival. The results in Table 10 show that the likelihood that an MFI will not survive increases significantly with an increase in the Donations. The regression

Table 9

Sample Selection – Heckman Two-stage Estimation.

<i>Stage 1: Probit regression</i>		<i>Stage 2: OLS Regression</i>	
Variables	Deposit dummy	Variables	Z-score
Deposits to Loans	1.595*** (0.0276)	Donations	−0.0930*** (0.0274)
Equity-assets ratio	−2.240*** (0.230)	Equity-assets ratio	5.886*** (0.735)
Interest margin	−2.119*** (0.380)	Interest margin	−0.0975 (1.068)
Cost ratio	−1.722*** (0.299)	Cost ratio	−3.112*** (0.897)
NPL ratio	8.092*** (2.243)	NPL ratio	−16.91*** (4.348)
GDPPC	−0.0107 (0.00715)	GDPPC	0.0216 (0.0150)
Inflation	−0.00345 (0.00538)	Inflation	0.00455 (0.0119)
Constant	−0.938***	IMR _{t-1}	−0.527*** (0.153)
		Constant	3.095*** (0.328)
Observations	7,543	Observations	363
Country & Year FE	Yes	Country & Year FE	Yes
Pseudo R-squared	0.533	Adj. R-squared	0.347

In the first stage model, we apply ‘deposit dummy’ as the dependent variable and estimate probit regression with the loan ratio as the exogenous regressor. We create the deposit dummy = 1 if an MFI’s deposit-to-assets ratio is more than 50 %. In the 2nd stage, we add IMR_{t-1} (Lag Inverse Mills Ratio) from the 1st stage and run the OLS regression with other controls on the stability proxy of the Z-score. The variables are the same as those in the baseline models. The values within parentheses are robust t-stats. The asterisks ***, **, and * denote significance at less than 1 %, 5 %, and 10 % levels.

Table 10

MFI Non-survival Probability Analysis.

Baseline model (Probit): $Prob(Y = 1 X) = \alpha + \beta \text{Log}(\text{donation to asset}) + \sum \gamma \text{Controls}_{it} + \varepsilon_{it}$			
We also test the findings’ consistency by estimating the Cox proportional and competing hazards models. These models have semiparametric characteristics that overcome the underlying issues related to data normality. Besides, these models can address the issues related to time-varying covariates and their proportionalities.			
Variables	Baseline model Probit model	Alternative models	
		Cox model	Competing hazards model
Donations	0.04*** (3.58)	0.09*** (7.09)	0.06*** (7.32)
Z-score	−0.09*** (−4.03)	−0.09*** (−5.38)	−0.09*** (−5.85)
Interest margin	−1.10*** (−3.32)	−0.96*** (−3.53)	−1.01*** (−5.00)
Cost ratio	1.57*** (4.92)	0.63*** (3.57)	0.91*** (5.91)
NPL ratio	10.37*** (3.57)	1.03 (0.59)	4.27*** (3.06)
GDPPC	0.02** (2.45)	0.05*** (7.76)	0.04*** (6.83)
Inflation	0.05*** (4.77)	0.03*** (8.27)	0.03*** (6.72)
Constant	1.02*** (6.80)	N/A	N/A
Observations	2,889	2,889	2,889
Country & Year FE	Yes	Yes	Yes
R-squared	0.07	N/A	N/A
Wald χ^2	131.34	282.55	336.71

The baseline Probit model tests if higher donations recipient MFIs have a higher probability of failure (i.e., survival periods < 20 years). The dependent variable is a dichotomous variable, where $Y = 1$ when an MFI’s survival period (i.e., total years of operations) is less than 20 years, 0 otherwise. *Donations* is the log of donated equity to total assets received by an MFI. The values within parentheses are robust z-stats adjusted for heteroscedasticity. The asterisks ***, **, and * denote significance at less than 1 %, 5 %, and 10 % levels.

coefficient is 0.04 and is statistically significant at the 1 % level. This result implies that the higher the level of donations used in relation to MFIs’ assets, the greater the probability that they will fail.

We further employ two probabilistic models, the Cox proportional hazards model (or Cox model) and the competing hazards model

Table 11
Donations and MFI survival – the Role of Stability.

Variables	Model 1 Survival periods	Model 2 Survival periods
Donations	−0.08* (−1.79)	0.15 (1.55)
Z-score	0.15** (2.08)	−0.06 (−0.58)
Donations *Z-score		−0.07** (−2.57)
Interest margin	2.31** (2.04)	2.46** (2.18)
Cost ratio	−2.67*** (−3.04)	−2.98*** (−3.44)
NPL ratio	−28.71*** (−3.87)	−28.63*** (−3.85)
GDPPC	0.02 (1.06)	0.02 (1.03)
Inflation	−0.12*** (−6.98)	−0.11*** (−6.91)
Constant	14.30*** (32.92)	15.00*** (29.15)
Observations	2,881	2,881
Country & Year FE	Yes	Yes
R-squared	0.05	0.05
F value	16.39	15.16

In model 1, we estimate $Survival\ periods_{it} = \alpha_i + \beta_1 Donations_{it} + \gamma Controls_{it} + \varepsilon_{it}$ by using the OLS estimator. In model 2, we estimate $Survival\ periods_{it} = \alpha_i + \beta_1 Donations_{it} + \beta_2 Z\text{-score}_{it} + \beta_3 Donations_{it} * Z\text{-score}_{it} + \gamma Controls_{it} + \varepsilon_{it}$ by using OLS estimator, where $Donations_{it} * Z\text{-score}_{it}$ is the interaction between Log of Z-score and log of donation to asset ratios. We run the Interaction Variable Misspecification Test suggested by Balli and Sørensen (2013). The results confirm the nonexistence of misspecification due to misspecified or nonlinear relationships. However, we opted not to include these results in the revised manuscript due to space constraints, but they are available upon request. The values within parentheses are robust t-statistics adjusted for heteroscedasticity. The asterisks ***, **, and * denote significance at less than 1 %, 5 %, and 10 % levels.

(or hazards model), to ensure consistency of the findings. These models are predominantly used to predict bank failure. However, we use these models in a new manner in the context of microfinance failure (or survival) analysis. Both models follow semi-parametric assumptions for the variables because the outcome of the variable's distribution is not essential for parameter estimation. Being a semi-parametric model, the Cox model, for instance, does not assume any parametric form for the baseline hazard function (Schaeck et al., 2009); thus, it helps predict the failure (or non-survival) of financial institutions (Lane et al., 1986). In contrast, the hazards model involves modeling the cause-specific hazard function of failure using the partial likelihood approach (Andersen et al., 1993). Hence, with some asymptotic variations, the models can address time-varying covariates and their proportionality issues.

The results of the Cox and hazard models are presented in the second and third columns of Table 10, respectively. Similar to the probit estimation, the alternative models' results indicate that an increase (decrease) in donations relative to MFIs' assets is associated with a decrease (increase) in survival probability. Accordingly, the probability estimates based on the three different methods unequivocally substantiate that MFIs are prone to fail when increased donations are used to support operations.

We also analyze the effect of donations on MFIs' survival using parametric OLS estimation, where we regress Donations against the survival period. The underlying idea of the investigation is to provide further understanding of the donation–MFI survival nexus by factoring in financial stability in the analyses. In the first model in Table 11, we regress Donations with survival periods¹⁰ of MFIs, controlling MFI stability (i.e., Z-score) with other MFI- and country-level variables. The results show a negative statistical significance at the 10 % level. This indicates that donations in MFIs' operations are inversely related to their survival span. In other words, MFIs' operational duration decreases proportionately with higher donation fund utilization in operations because of lower financial stability. In the second model, we enter an interaction variable that multiplies the donation and stability variables. The interaction variable (Donations * Z-score) shows a negative coefficient ($\beta = 0.07$), statistically significant at the 5 % level. This interaction result implies that higher donations significantly reduce the survival period of MFIs by rendering them less stable.

Finally, we contend that MFIs' governance can play a vital role in reducing the probability of failure, as corporate governance plays an influential role in lessening the financial distress of an institution (Bravo-Urquiza & Moreno-Ureba, 2021). We consider two aspects of corporate governance: board size and female board members. In general, board size increases in response to the scale and complexity of an institution (Germain et al., 2014); thus, a larger board indicates the expansion of an MFI and a lower probability of failure. In addition, higher female representation on the board suggests more diversification; thus, combining various perspectives and

¹⁰ Total years of operations of an MFI since its inception.

Table 12
MFI Non-survival – the Role of Governance.

Variables	Non-Survived MFIs
Donations	0.062*** (2.881)
Board Size	−0.217*** (−2.607)
Female Board Members	−0.021 (−0.093)
Interest Margin	−1.167* (−1.798)
Cost ratio	2.462*** (4.505)
NPL ratio	19.247*** (3.312)
GDPPC	0.046*** (2.749)
Inflation	0.111*** (6.033)
Constant	1.124*** (3.789)
Observations	1,197
Country & Year FE	Yes
Pseudo R-squared	0.14
Wald χ^2	87.30

The model tests if the governance variables reduce the probability of MFI failure (i.e., survival periods < 20 years). The dependent variable is a dichotomous variable, where $Y = 1$ when an MFI's survival period (i.e., total years of operations) is less than 20 years, 0 otherwise. *Board Size* is the total number of members on the board, and *Female Board Members* is the ratio of female board members to total members on the MFIs' board. The values within parentheses are robust z-stats. The asterisks ***, **, and * denote significance at less than 1 %, 5 %, and 10 % levels.

experiences may contribute to better monitoring (Reiff & Tykvová, 2021).

The findings in Table 12 show that both governance variables have a negative relationship with the non-survival probability of MFIs. Although the female board member variable does not show a statistically significant impact on the dependent variable, the effect of the governance variables remains negative. Hence, it provides statistical evidence supporting our earlier postulation that a robust governance mechanism can help reduce MFI failures. Conceivably, strong governance can help MFIs survive in the long run by allowing them to manage donations efficiently to minimize the negative impact on their survival. Accordingly, there is a strong possibility that some will remain operational over the years because of the strength of internal governance, whereas others will fail.

5.7. Discussion

Our findings provide the first empirical evidence of the impact of donation funding received by MFIs on their financial stability. This study extends our understanding of the role of donations in the survival of MFIs. In line with the theoretical argument that MFIs essentially operate as financial intermediaries, similar to banks, our study considers a unique aspect of the MFI intermediation process: the transformation of donation funds to microloans. The findings of this study demonstrate that donations have deleterious effects on the stability of MFIs, even though they are crucial funding sources for their credit operations.

While prior studies emphasize that donors tend to allocate funds to MFIs demonstrating stronger financial health and reputational standing (Trussel & Parsons, 2007; Tchuigoua, 2014), our study approaches the issue from a complementary perspective. Specifically, we investigate how donations, once received and integrated into the institution's funding model, influence long-term financial stability. This aligns with the argument of existing studies (Hartarska & Nadolnyak, 2007; Cull et al., 2011; Mersland & Strøm (2010) that largely point out that transformed (i.e., regulated) MFIs tend to achieve better financial outcomes than their NGO counterparts (Hartarska & Nadolnyak, 2007; Cull et al., 2011). Our descriptive analysis (see Appendix C) supports this by showing that NGO and not-for-profit MFIs report higher average reliance on donations than other legal forms. Thus, our findings complement the existing literature by shedding light on the possible ex post financial implications of sustained donor reliance, specially in the early or transitional phases of an MFI's institutional lifecycle. This adds the verified perspective from our empirical results to the broader policy debate by revealing that while donations may initially flow to stronger institutions, they may also introduce structural vulnerabilities that erode financial resilience over time.

To better understand the temporal dynamics of donation inflows, we examine the average donation-to-asset ratio of MFIs over time. Appendix F illustrates the global average of this ratio across years, along with a ± 1 standard deviation band capturing the volatility of donation flows. The figure reveals considerable fluctuations, supporting our view that donations, while not reimbursable, are often

unstable and irregular funding sources. This pattern underpins our core argument that MFIs' reliance on donations can amplify financial risk due to planning uncertainty and inconsistent capital inflows. We contend that volatile donation funding makes MFIs financially unstable because they are linked to higher operational costs (Gonzalez, 2010a; Zamore et al., 2021) in their eccentric business models. The high disbursement and monitoring costs of lending to low-credit-worthiness marginal borrowers are major impediments to MFIs achieving financial stability. Owing to this intrinsic flaw, cost-free donation funding is not helpful for their survival and continued operation as financially viable institutions, even if donations are one of the primary funding sources (Afrifa et al., 2019). Conversely, donations make them unstable.

To understand the mechanisms behind the observed negative relationship between donations and financial stability, we decompose the Z-score into its key components: profitability (ROA), capitalization (Equity-to-Assets), and earnings volatility (σ ROA). Our decomposition results, presented in Panel A of Appendix D, reveal that Donations are positively associated with the equity-assets ratio, suggesting that better-capitalized MFIs may have greater access to donor funding. This aligns with the view that donors prefer to support financially sound institutions. However, Donations are also negatively associated with ROA, indicating that MFIs with higher reliance on donations tend to be less profitable, potentially due to inherent higher operating costs or a higher cost ratio. Again, the donations are found to be negatively related to σ ROA – the decline in average returns outweighs any marginal reduction in volatility, ultimately lowering the Z-score. Overall, this decomposition indicates that the negative effect of Donations on the Z-score is driven primarily by depressed profitability, which outweighs the capital enhancement. These findings provide a clearer picture of how donations shape institutional risk profiles and contribute to fragility.

To further probe the channel through which donations affect institutional stability, we also tested the impact of donations on portfolio quality, proxied by the NPL ratio, given that weaker portfolio quality directly contributes to higher earnings volatility and hence lower stability. As shown in Panel B of Appendix D, higher donation levels are significantly associated with higher NPL ratios. This result suggests that donations may weaken loan monitoring incentives or encourage riskier outreach, ultimately leading to portfolio deterioration. Taken together, both the Z-score decomposition and the alternative NPL specification highlight that donation, while improving capitalization, tends to reduce profitability and weaken credit discipline. These effects jointly contribute to the erosion of financial stability through earnings-related risk (ROA and σ ROA) and deteriorating portfolio quality. These findings underscore the importance of assessing the broader institutional consequences of donor dependence, especially when stability and long-term sustainability are at stake. These results align with our earlier discussion on the role of high operating costs and earnings volatility in driving the adverse stability outcomes.

To further validate whether the adverse effect of donations on MFI stability reflects ex-post operational inefficiencies, we conduct a lag-based regression to examine whether financial instability intensifies in the years following donation inflows. This approach helps identify whether donation-induced vulnerabilities emerge gradually over time. The results, presented in Panel C of Appendix D, reveal that the coefficient for the one-year lag of the Donations (L1_Donations) is negative but statistically insignificant, while the two-year lag (L2_Donations) shows a significantly negative relationship with the Z-score. This pattern suggests that the destabilizing effects of donations may not materialize immediately but accumulate and become more pronounced over time. In line with our theoretical framework, this delayed impact may reflect increased operational rigidities, reduced cost discipline, or the gradual erosion of performance incentives. Taken together, these lagged effects reinforce the interpretation that donor funding, while potentially beneficial in the short term, can undermine long-term financial resilience by fostering structural inefficiencies and weakening managerial discipline.

Altogether, we find that MFIs' donation dependence leaves them financially unstable and has further implications for their continuity. MFIs may grow over time and attain financial strength by offering financial services to their clients. However, if they continue to depend on donation funding, which is initially a viable funding strategy, it threatens their existence in the long run. We observe that donations substantially increase the likelihood of failure. Furthermore, the probability of non-survival is critically related to the financial instability stemming from reliance on donations.

Thus, our study clarifies some crucial aspects previously overlooked in the microfinance literature. We assert that the financial stability of MFIs is unique compared to other financial intermediaries. Conventional financial institutions such as banks are entirely profit-oriented, and their financial stability is mainly dependent on their yield from operations. MFIs, however, face the dilemma of balancing their social goals (i.e., outreach) and financial goals (i.e., financial sustainability). While this complexity is acknowledged in the literature (Cull et al., 2007; Hermes et al., 2011), we provide direct evidence that the problem has more extensive implications, reducing MFIs' self-sufficiency and causing them to collapse. Consequently, the core goals of donation-enhancing outreach and inclusion (El-Zoghbi & Gähwiler, 2013) are likely to be jeopardized. The rational basis for such a contention is that a financial institution that cannot achieve the goals essential for its own sustenance may find it challenging to fulfill its social and economic commitments.

The negative impact of donations on MFI stability and non-survival is not limited to the niche microfinance sector but also has profound implications for financial markets and the economy, considering their role in credit expansion through financial inclusion (López & Winkler, 2019). The role of MFIs as financial intermediaries has been integrated into the overall financial systems of many countries (Schulte & Winkler, 2019). Thus, like other financial intermediaries, a well-functioning microfinance sector can strengthen its financial and economic systems by efficiently managing its funds and financial investments, whereas instability can disrupt proper resource allocation and negatively impact economic growth (Claessens & Laeven, 2005; Creel et al., 2015). Interestingly, from our country and geographic subsample analysis, we observe that the adverse impact of donations on MFI sustainability remains generally homogenous, with some negligible exceptions. Hence, if MFIs cannot sustain themselves as stable financial institutions, they can negatively impact the entire financial system of the countries in which they operate (Schulte & Winkler, 2019).

Another interesting aspect of our findings comes from the subsample analysis based on MFI profit orientation, which indicates that donations negatively impact both types of institutions. However, its relative influence on the stability of for-profit MFIs is marginally

lower. Although variations are trivial, this may arise from the fact that profit-oriented MFIs focus on achieving more cost-effective operational efficiency (Leite et al., 2019). This finding further supports our conceptual assertion that donations affect MFI stability through the cost channel. Considering their financial stability, the debate on whether MFIs should prioritize financial goals (for-profit orientation) over social goals (non-profit orientation) is inconsequential if microfinance operating costs cannot be curtailed. In this scenario, the role of donations is pivotal, as MFIs receiving fewer donations become more cost-effective over time (Caudill et al., 2009).

6. Conclusion

MFIs were created to provide financial services to the marginal sectors of society, which the traditional banking sector largely overlooks. Due to the motivation to “serve the poor,” MFIs are often treated as development organizations, whereas their business model essentially characterizes them as financial intermediaries like banks. Although MFIs have become important financial intermediaries in many countries, they still focus on the niche marginal client base, where outreach and inclusion are the primary objectives. MFIs, thus, as key players in financial intermediation, aim to balance their dual objectives of social outreach and financial sustainability. However, their reliance on donations introduces structural vulnerabilities that influence their long-term viability. While the social motivation for donations is straightforward, its impact on MFIs as financial institutions has remained mostly unexplored. This research highlights the complexities of the transformation mechanism through which donations fund microfinance operations by applying theoretical lenses such as agency theory, moral hazard, and operating leverage. Accordingly, we examine whether and how MFIs’ reliance on donation funding affects their financial stability.

We use unbalanced panel data on 2653 MFIs from 119 countries over a 20-year (1999–2018) period to test the impact of donations on MFI stability. We first test this relationship using the OLS estimator and find that donations significantly and negatively affect MFI stability. We then employ two different panel data estimators, FE and GMM, to test the reliability of our OLS estimation inferences. They provide similar findings in that donations render MFIs financially unstable. We examine the differences across other dimensions, such as MFI profit orientation, legal status, and geographic and country variations, to determine the possible weaknesses intrinsic to this relationship. However, we find negligible variation and conclude that donation funding is fundamentally disadvantageous for MFI stability. Considering the close connections between the stability and survival of financial institutions, we also extend our analysis to examine whether business continuity has any connection to the donations the MFIs receive. Consistent with our stability analysis, we find that the likelihood of MFI non-survival is significantly associated with a higher donation level. By analyzing the interactive effects of donations and stability, we show that MFI survival periods shorten as more donations are channeled by lower financial stability.

Our study pioneers the establishment of a direct link between donations and MFI stability, increasing the modest body of existing literature focusing on this phenomenon. It sheds new light on the role of donations in stability. To our knowledge, this is the first comprehensive investigation and analysis of the survival of MFIs. First, we expand the literature on survival analysis from a new perspective, which is predominantly available for bank survival analysis in the past. Conversely, the MFI (non-) survival analysis considerably enhances the value of our findings regarding the role of donations in the microfinance sector.

The results of this study have several important implications for future policy and practice. The damaging impact of donations on MFI stability and survival is a vital concern for managers planning credit operations. For a business to survive as a stable financial entity, it must concentrate on being operationally cost-efficient rather than seeking cost-free donation funds. Likewise, regulators should develop policies to support MFIs in becoming more cost-effective and regulate MFI lending more prudentially. Furthermore, donors need to rethink the mechanism of serving the poor through the intermediation of MFIs, because their social goal of inclusive financing may negatively affect the economy and society by creating unstable financial institutions. They need to be more vigilant in selecting MFIs, which should produce a convincing financial plan, demonstrate their corporate health, and ensure that they do not become over-dependent for too long. Altogether, they need to confirm that an efficient mechanism is in place, while enabling them to achieve their philanthropic goals.

Given the adverse effect of donations on financial stability, MFIs and donors must consider more balanced funding models that reduce overdependence on uncertain, cost-free capital. A promising strategy is to adopt hybrid funding models that combine grants with market-based sources, such as retained earnings, deposits, or commercial borrowing (Cull et al., 2011). These models can enhance financial discipline while maintaining outreach to vulnerable populations. Moreover, performance-based donations, where grants are tied to clear impact or sustainability metrics, can improve resource accountability and reduce the agency problems between donors and MFI managers (Périlleux et al., 2012). Regulatory frameworks should also incentivize transparent reporting and prudent leverage management in MFIs to mitigate systemic risks.

While our study provides a novel perspective to MFI research with first-hand evidence, as with any empirical study, our research has its limitations. The MIX Market dataset, though the most comprehensive global source, relies on voluntary reporting and may therefore reflect selection bias or self-reporting errors. This limitation is not unique to our study, but the dataset’s breadth, time span, and global coverage justify its use. A clean pre-/post-donation baseline is also infeasible, as MIX lacks consistent early donation data, making the first year of receipt indeterminable. Our approach, therefore, prioritizes robustly observable donation flows and stability outcomes across the full panel. In addition, we cannot capture non-financial dimensions – such as institutional reputation or transparency (e.g., MIX diamond ratings) – that may influence both the receipt and use of donations. Finally, while alternative instruments such as regional donor inflows or country-level aid dependency would be valuable robustness checks, consistent panel variation of such variables across 119 countries is lacking in our empirical setup, limiting feasibility. Future research could address these gaps with richer regulatory or country-specific datasets.

Our approach to linking donations with MFI stability will provide a stimulus for future researchers. If the debate is to advance, a better understanding of the optimal use of donations must be established. Further research could be conducted to determine the

donation threshold and whether an optimal donation level can positively or negatively influence MFI stability. A natural progression for this work would be to undertake a threshold analysis for different types of MFI, as we have performed a linear analysis in this study. Besides, an important direction for future research would be to conduct a comparative analysis between MFIs that rely on donations and those that do not. Specifically, examining whether MFIs that receive donations are more vulnerable to financial distress or institutional failure relative to non-donation-based MFIs could provide deeper insights into how funding structures influence long-term sustainability. Such an analysis, however, would require a broader framework and data architecture beyond this paper's current scope. Furthermore, cost efficiency in MFI operations is an intriguing issue that can be explored in future research across a broader range of financial institutions. Finally, we encourage future research to investigate whether hybrid or conditional funding structures can buffer MFIs against earnings volatility and institutional failure over time. Comparative studies across different institutional and regional settings would further enrich the understanding of sustainable microfinance funding strategies.

CRedit authorship contribution statement

Md Hamid Uddin: Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Masnun Al Mahi:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization. **Shabiha Akter:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization. **Sabur Mollah:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Jia Liu:** Writing – review & editing, Methodology, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.intfin.2025.102244>.

Data availability

Data will be made available on request.

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