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International Journal of Finance & Economics

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RESEARCH ARTICLE OPEN ACCESS

How Does Vulnerability Framing by Microfinance Institutions Leverage Funding Success in Crowdfunding?

Ana Paula Matias Gama[1] | Ricardo Emanuel-Correia[2] | Fábio Duarte[3] | Mário Augusto[4]

[1]University of Beira Interior, Instituto Universitário de Lisboa (ISCTE-IUL), Business Research Unit (BRU-IUL), Lisbon, Portugal | [2]Instituto Superior de Contabilidade e Administração de Lisboa (ISCAL), Instituto Politécnico de Lisboa, Instituto Universitário de Lisboa (ISCTE-IUL), Business Research Unit (BRU-IUL), Lisbon, Portugal | [3]School of Economics and Management, and cef.up, University of Porto, Porto, Portugal | [4]University of Coimbra, CeBER, Faculty of Economics, Coimbra, Portugal

Correspondence: Ricardo Emanuel-Correia (recorreia@iscal.ipl.pt)

Received: 6 September 2024 | **Revised:** 22 December 2025 | **Accepted:** 29 December 2025

Keywords: crowdfunding | framing theory | microfinance institutions | prosocial finance | vulnerability framing

ABSTRACT

This study draws on framing theory to investigate how microfinance institutions (MFIs) strategically construct a vulnerability-oriented organisational identity and how this framing influences their funding decisions during the pre-campaign phase of prosocial crowdfunding. Using a unique dataset of 334,852 microloans issued by 140 MFIs across 59 countries on the Kiva platform, we distinguish between MFIs exclusively listed on Kiva and those also featured on Mix Market. Our findings reveal a pronounced funding bias among MFIs that do not emphasise vulnerability in their framing. In contrast, MFIs that adopt a prognostic vulnerability frame tend to reverse this bias—particularly those solely reliant on Kiva. While both types of MFIs demonstrate some capacity to mitigate funding inequality, the effect is significantly more pronounced among those exclusively listed on Kiva. Our results also point to a potential mission drift, possibly incentivised by Kiva's vulnerability badge system, which may reward financial stability over genuine outreach to vulnerable borrowers. Overall, the findings underscore the central role of institutional framing in shaping MFIs' funding strategies and access to capital for marginalised entrepreneurs in the pre-campaign phase.

> *If we are looking for one single action which will enable the poor to overcome their poverty, I would go for credit. [...] If we can come up with a system which allows everybody access to credit while ensuring excellent repayment—I can give you a guarantee that poverty will not last long*
>
> [Yunus (1994)]

1 | Introduction

Entrepreneurs in developing economies often struggle to secure capital due to the perceived high risk they represent and insufficient collateral required by traditional financial institutions (Bruton et al. 2015; Khavul 2010). This challenge is particularly pronounced during early-stage funding (Frydrych et al. 2014), a critical phase when resources are scarce (Churchill and Lewis 1983) and is further exacerbated by systemic biases—particularly against women, who often face loan ceilings and discriminatory lending practices (Ongena and Popov 2016; Agier and Szafarz 2013).

In this context, crowdfunding has emerged as a transformative financing mechanism, enabling entrepreneurs to bypass conventional barriers by directly engaging with a broad base of potential backers. The global crowdfunding market, valued at $19.9 billion in 2023, is projected to reach $72.8 billion by 2032 (Polaris Market Research 2024). Within this ecosystem,

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prosocial crowdfunding platforms such as Kiva have gained prominence, facilitating over $1.5 billion in loans to more than 3.8 million borrowers (Kiva 2021a) and opening new pathways to financial inclusion.

Accessing crowdfunding, however, is not neutral. It is influenced by lender perceptions, borrower narratives and the characteristics of microentrepreneurs, such as gender, rural location, or group affiliation (Agier and Szafarz 2013). Within this landscape, a distinctive prosocial crowdfunding model has emerged—based on charitable lending rather than profit-seeking (Anglin et al. 2020). Kiva stands out as the largest prosocial crowdfunding platform, operating through a model of intermediation where Microfinance Institutions (MFIs) act as gatekeepers. These MFIs select and disburse loans to microborrowers in the pre-campaign phase, post the loan on the Kiva platform for public funding in the campaign phase and oversee loan repayment in the post-campaign phase.

Despite its importance, the pre-campaign phase remains largely underexplored in the crowdfunding literature, which has predominantly focused on campaign and post-campaign dynamics (e.g., Mollick 2014; Allison et al. 2015). This early institutional stage is where MFIs exercise the greatest discretion—selecting borrowers, defining loan amounts and constructing vulnerability frames that shape lender perceptions once campaigns become visible. Recent studies emphasises the relevance of such early-stage institutional behaviour for understanding crowdfunding outcomes (e.g., Kim and Viswanathan 2019; Hui et al. 2014; Colombo et al. 2015).

Kiva allows MFIs to refinance loans at zero interest, requiring only the repayment of principal to Kiva's charitable lenders. In exchange, Kiva requires its partners to demonstrate strong social commitment, awarding them 'social performance badges' to signal their focus areas—such as the 'Vulnerability-Focus Badge'. These badges can enhance fundraising success by appealing to lenders' prosocial motivations (Figueroa-Armijos and Berns 2022). However, as competition for Kiva's subsidised capital intensifies (Ly and Mason 2012a), some MFIs—especially those also listed on Mix Market—may recalibrate priorities toward financial sustainability, potentially compromising their social mission (Hishigsuren 2007; Mersland and Strøm 2010). This tension raises an important question: Does the vulnerability framing adopted by MFIs mitigate or reinforce funding biases during the pre-campaign phase?[1] To explore this, we distinguish between two institutional types: (1) MFIs exclusively listed on Kiva, and (2) MFIs also listed on Mix Market. The rationale for this distinction lies in the financial flexibility and visibility of Mix Market-listed MFIs, which have access to diversified capital sources, including deposits and microfinance investment vehicles (MIVs) (Bogan 2012). These institutions may therefore be less reliant on Kiva loans and potentially less driven by anti-poverty objectives in their operational models.

This distinction is central to our understanding of vulnerability bias, which we define as the tendency of MFIs or platforms to favour—or disadvantage—borrowers based on perceived vulnerability characteristics such as gender, rural status, or participation in group lending. While prior research has examined the motivations of lenders (e.g., Allison et al. 2015; Berns et al. 2020; Defazio et al. 2021), the behaviour of MFIs at the pre-campaign phase remains significantly underexplored (Gama et al. 2023; Shettima and Dzolkarnaini 2024).

Grounded in framing theory, this study investigates how MFIs strategically frame their organisational identity—specifically their vulnerability orientation—to influence pre-campaign funding decisions. Framing theory provides a relevant lens to examine how institutions communicate their values and missions to structure interpretation and guide action, particularly when addressing marginalised populations.

Our focus is on business loans,[2] which differ from personal loans in that they are income-generating but also riskier for lenders (Gafni, Marom, et al. 2021; Moleskis et al. 2019). This allows for a clearer test of MFIs' social intentions.

Our findings show that MFIs that do not adopt a vulnerability-focused framing exhibit systematic funding bias. In contrast, MFIs that explicitly frame their mission around supporting vulnerable groups—female borrowers, rural clients and group lending campaigns—tend to reverse this bias, particularly when they are exclusively listed on Kiva. However, Kiva's practice of awarding the vulnerability badge uniformly across MFIs, regardless of institutional constraints or financial strategies, may inadvertently encourage mission drift.

The remainder of this paper is structured as follows: Section 2 discusses crowdfunding and microentrepreneur financing. Section 3 presents the theoretical background and hypotheses. Section 4 describes the research design. Section 5 presents the findings. Section 6 offers a discussion of the results. Section 7 concludes with key contributions, limitations and implications for policy and practice.

2 | Crowdfunding and Microentrepreneurs Financing

Acquiring resources is one of the most vital entrepreneurial tasks in the process of venture creation (Chliova and Ringov 2017). Crowdfunding broadly refers to the effort by entrepreneurs to fund their ventures by collecting small contributions from a relatively large number of individuals via the internet (Mollick 2014). Leveraging technological advances, crowdfunding platforms democratise access to finance by directly connecting entrepreneurs with global investors (Khachatryan et al. 2017) and have become one of the most important tools for lifting individuals out of poverty (Armendariz and Labie 2011; Postelnicu and Hermes 2018).

With the advent of the internet, several crowdfunding models have emerged, including: lending-based crowdfunding (where funders receive a contractually agreed interest and repayment of principal), equity-based crowdfunding (in which backers provide capital in exchange for a return on investment), reward-based crowdfunding (where backers receive non-pecuniary benefits) and donation-based crowdfunding (involving philanthropic giving with no expected return) (Berns et al. 2020). More recently, prosocial crowdfunding has emerged, where lenders provide credit to support individuals in need, often motivated

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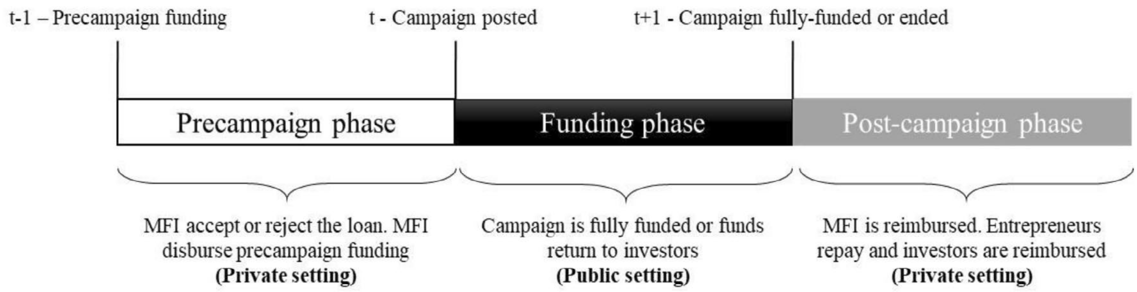

FIGURE 1 | Funding timeline in crowdfunded prosocial microfinance.

by emotional and altruistic returns (Allison et al. 2013; Berns et al. 2020).

Among prosocial platforms, Kiva stands out—alongside others such as Lendwithcare, Zidisha, Rang De and Readyfor—as a leader in connecting microentrepreneurs in developing countries with global lenders. This is achieved through a structured system where MFIs act as intermediaries (Allison et al. 2013). Kiva's funding process operates in three distinct phases. In the pre-campaign phase, MFIs screen applicants, pre-fund loans and assist borrowers in crafting online profiles to attract lenders (Meyskens and Bird 2015). In the funding phase, campaigns are launched under an 'all-or-nothing' model, requiring full funding within 30 days; otherwise, lenders are reimbursed. The post-campaign phase involves loan monitoring and repayment, with MFIs providing transparent updates to lenders (Dorfleitner et al. 2021). This cyclical process allows MFIs to refinance operations by recycling repaid funds into new loans, sustaining a continuous flow of capital to vulnerable borrowers (Galak et al. 2011; Anglin et al. 2020). Figure 1 summarises this funding timeline.[3] Our analysis focuses specifically on the pre-campaign phase, which provides a more private decision-making setting, allowing for a clearer examination of potential bias in funding allocations to vulnerable borrower groups.

Kiva pursues a strong social mission and applies specific criteria for selecting partner MFIs. These include a social performance scorecard that assigns badges such as 'Vulnerability', indicating that an MFI provides particularly small loans to underserved populations.[4] Kiva also applies minimum financial requirements, such as standards for asset value, portfolio size and quality and transparency over interest rates charged (Dorfleitner et al. 2020). This selection framework reflects the logic of hybrid MFIs, which combine development goals with banking discipline to ensure operational sustainability (Battilana and Dorado 2010). By prefunding borrowers and later recovering capital from lenders, Kiva offers a scalable solution to circumvent traditional financial exclusion.

On the Kiva platform, entrepreneurs may apply for business loans (aimed at income-generating activities) or personal loans (used to cover basic needs such as healthcare or education). Prior research shows that personal-purpose loans represent a minority of Kiva's portfolio—Gafni, Hudon, and Périlleux (2021) and Moleskis et al. (2019) report respective shares of 9% and 8.6%. Our analysis focuses exclusively on business loans, which have the potential to generate additional income and empower vulnerable entrepreneurs (Bruton et al. 2015), albeit with a higher level of risk for lenders.

The expansion of crowdlending has opened new opportunities for microfinance organisations to compete for capital subsidised by individual generosity (Bishop and Green 2010). Kiva lenders recover only the loan principal and forgo any financial return, allowing MFIs to access zero-interest debt. However, as pressure grows for MFIs to reduce subsidy dependence (Hoque et al. 2011), financial performance becomes a critical priority. A shift toward a more commercial orientation can lead to problematic practices, including excessive interest rates (Morduch 2020), speculative investments (Cull et al. 2009) and heightened borrower pressure that disrupts informal social networks (Attanasio et al. 2015).

In this context, some MFIs also opt to list on Mix Market, a global database promoting transparency through standardised financial disclosures. Listing enhances institutional visibility to investors and facilitates access to alternative, often lower-cost sources of funding—such as deposits or subsidised debt from MIVs (Bogan 2012). As a result, these MFIs are likely to be less dependent on Kiva's zero-interest capital, and their commitment to poverty alleviation may play a relatively smaller role in shaping their business models. Supporting this trend, Cull et al. (2018) document a third consecutive year of decline in the number of extremely poor clients served globally, pointing to a clear pattern of mission drift.

Nonetheless, mature MFIs may still benefit from Kiva's model. Kiva loans are denominated in hard currency, with currency risk transferred to lenders (Sousa-Shields and Frankiewicz 2004). Moreover, the platform enables MFIs to shift default risk to social investors (Mersland and Urgeghe 2013), reducing the financial impact of borrower non-repayment.

To explore how these institutional dynamics influence funding decisions, we investigate potential vulnerability bias in the pre-campaign phase by dividing MFIs into two groups: those exclusively partnered with Kiva and those also listed on Mix Market.

3 | Theoretical Background and Hypotheses Development

3.1 | Framing Theory

Framing theory is an important framework in the decision-making literature. It explains how individuals construct meaning within a given context (Tversky and Kahneman 1981). In the context of crowdfunding, scholars have only recently begun to investigate the implications of framing in lenders'

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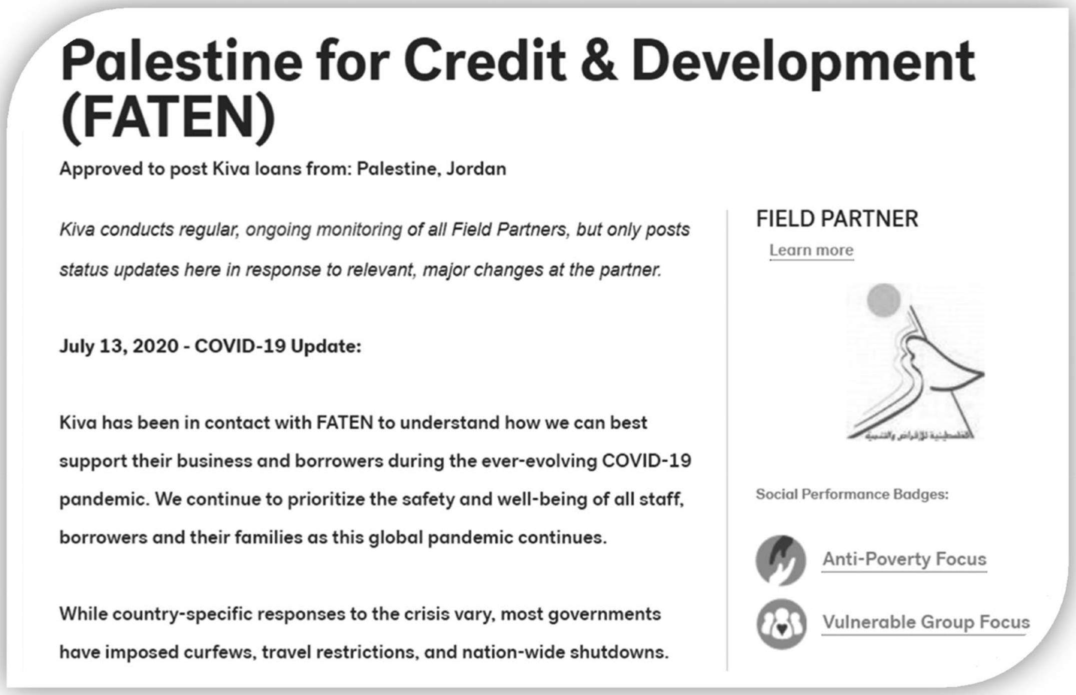

FIGURE 2 | MFI page view: Example with the 'Vulnerability' badge.

decision-making processes (e.g., Allison et al. 2015; Defazio et al. 2021; Figueroa-Armijos and Berns 2022). However, limited attention has been paid to how vulnerability framing influences decision-making in prosocial crowdfunding.[5]

Vulnerability refers to 'the capacity of poor people to meet their needs on a regular and assured basis' (Kabeer 2005, 4710). As it both influences and is influenced by income-generating processes, vulnerability can be viewed as both a cause and a consequence of poverty (Morduch 1994). Reducing vulnerability is thus a fundamental goal of prosocial crowdfunding initiatives within online microfinance (Figueroa-Armijos and Berns 2022). In these settings, entrepreneurs receive funding from amateur investors who contribute small amounts—forming a relationship based more on 'online trust' than on formal contractual arrangements. Consequently, the framing of information becomes critical in shaping emphasis and perceptions (e.g., Defazio et al. 2021).

The organisation and presentation of prosocial cues in the entrepreneur's profile can significantly influence project success by emphasising specific social goals. These cues can activate a sense of individual social responsibility in potential lenders, which in turn may enhance funding success. To align with lender expectations, microborrowers often craft narratives that portray themselves as vulnerable. This framing strategy has proven effective in securing funding. For instance, entrepreneurs strategically employ specific language in campaign descriptions (Allison et al. 2015). Kaminski and Hopp (2020) demonstrate that positive psychological language becomes particularly salient in contexts where objective information may be perceived as intimidating, and lender preferences are ambiguous. Moss et al. (2018) further show that campaigns using a single linguistic category that emphasises the social over the economic dimension tend to be funded more rapidly. Su et al. (2024) found that subtle variations in linguistic framing—such as the use of 'want' versus 'need'—significantly influence positive outcomes from lenders.

Hence, lending decisions often revolve around perceived borrower vulnerability, particularly among target groups such as female entrepreneurs, collective borrower groups (Dorfleitner et al. 2021) and rural borrowers (Figueroa-Armijos and Berns 2022). Taken together, these studies suggest that the way MFI frame borrower vulnerability during the pre-campaign phase has a substantial impact on campaign success.

An ongoing debate centres on whether MFI funding genuinely enhances financial access and inclusivity for vulnerable borrowers (e.g., Mersland et al. 2019). Some studies argue that despite their poverty-alleviation missions, MFIs may unintentionally undermine successful funding outcomes (e.g., Figueroa-Armijos and Berns 2022).

The Kiva platform addresses this concern by assigning social performance badges to MFIs with a focus on vulnerable groups. This information is prominently displayed in the upper right corner of each MFI's profile page, which is directly linked to the campaign page (Kiva 2025). Figure 2 illustrates a representative MFI page as seen by lenders, highlighting the designation of a 'Vulnerable Group Focus' badge. This identity suggests a prioritisation of individuals who can be portrayed as personally vulnerable, rather than those who appear self-sufficient.

MFIs have also faced criticism for potential mission drift. For example, Cull et al. (2009, 2011), examining the role of supervision, reported that MFIs often maintain profitability while reducing outreach to women and poorer clients when faced with stricter

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oversight. In contrast, institutions with a weaker commercial focus tend to sacrifice profitability to preserve outreach. A growing body of research has provided robust evidence of how MFI behaviour diverges from desired social outcomes over time (e.g., Mersland and Strøm 2010; D'Espallier et al. 2017; Beisland et al. 2019; Mersland et al. 2019). Nevertheless, there remains a lack of evidence on how vulnerability-framed MFIs behave in their lending practices during the private pre-campaign phase.

In this study, we explore this behaviour by distinguishing between vulnerability-framed MFIs listed solely on Kiva and those that are also listed on Mix Market. The rationale behind this categorisation is that visibility on Mix Market may grant MFIs access to alternative sources of funding, such as government grants and deposits.

3.2 | Hypotheses Development

3.2.1 | Gender Funding Bias and the Role of Vulnerability-Framed MFIs

The role of gender in resource acquisition has been extensively researched and remains a crucial policy concern (e.g., Renko et al. 2016; Uzuegbunam and Uzuegbunam 2018). Various gender-based differences help explain why women differ from men in their ability to mobilise financial resources. Wu and Chua (2012) identify disparities in interest rates, while Eddleston et al. (2016) highlight stricter documentation requirements and bank financing standards. Crowdlending has emerged as a potential solution to alleviate credit constraints (Bruton et al. 2015), providing capital from individuals beyond charitable motives (Anglin et al. 2020).

As competition for subsidised capital intensifies, *mission drift* becomes a concern: MFIs may gradually shift their focus from social to financial objectives, reducing outreach to female clients. While empirical evidence indicates that prosocial crowdlending platforms tend to favour—offering them greater support and exposing them to fewer social barriers (Kaufman et al. 2013) or even no discrimination at all (D'Espallier et al. 2011)—this support is not consistent across loan types. Gafni, Hudon, and Périlleux (2021), for example, show that loans requested on Kiva to women for basic needs are more readily funded, but this advantage diminishes when the loans are aimed at business ventures. Despite women comprising 80% of Kiva borrowers, only 30% of loans are allocated to female entrepreneurs operating in traditionally male-dominated sectors such as agriculture, wholesale, transportation, manufacturing and construction (Kiva 2023). These lending patterns—whether voluntary or not—may have adverse consequences, potentially discouraging women from pursuing income-generating activities, undermining their individual economic empowerment (Garikipati 2008), and weakening their decision-making power within households and society (Huis et al. 2019).

We therefore question how vulnerability-framed MFIs shape women's online business campaigns during the pre-campaign phase to differentiate them from other campaigns and enhance fundraising success. In the pre-campaign phase, MFIs select borrowers and craft their profiles to be published on Kiva. Framing entails emphasising specific aspects of perceived reality to make them more salient in communication. As such, the way entrepreneurs and MFIs construct and present campaign narratives plays a crucial role in influencing lending decisions (Defazio et al. 2021; Kuo et al. 2022).

When framing women's profiles, MFIs often employ tailored narratives (e.g., video pitches) to capture the attention of prosocial lenders. In information-sparse environments—where investors rely heavily on personal preferences—narratives and images that convey neediness and vulnerability (Jenq et al. 2015), along with positive entrepreneurial language, are more likely to appeal to lenders (Kaminski and Hopp 2020; Moss et al. 2018).

We argue that vulnerability-framed MFIs can increase fundraising success by strategically constructing women's business campaigns with detailed information about both the entrepreneur and her venture. Emphasising how income-generating activities contribute to family well-being can significantly enhance the attractiveness of these campaigns. Prosocial lenders are particularly responsive to initiatives with clear impacts on household income and assets (Garikipati 2008), especially when women are seen as investing in sustainable development and the well-being of their children (e.g., education, health) (Eddleston et al. 2016). Accordingly, MFIs may shape their organisational identity to align closely with female borrowers, especially as social returns are valued by Kiva's investor base (Hogg et al. 1995; Hogg and Terry 2014; Rodriguez-Ricardo et al. 2018).

Organisational identity strongly influences decision-making behaviour, helping explain why some MFIs adopt preferential framing strategies for particular borrower groups. We therefore argue that vulnerability-framed MFIs are more likely to frame income-generating campaigns by women in ways that maximise their visibility and access to subsidised capital on Kiva. This effect should be more pronounced for MFIs listed exclusively on Kiva, given their greater dependence on zero-interest debt from the platform. Formally, we hypothesise that:

H1. *Vulnerability-framed MFIs positively moderate the relationship between gender and the amount funded during the pre-campaign phase of prosocial crowdfunding.*

H1a. *Vulnerability-framed MFIs that are exclusively listed on Kiva positively moderate the relationship between gender and the amount funded during the pre-campaign phase of prosocial crowdfunding.*

H1b. *Vulnerability-framed MFIs that are also listed on Mix Market positively moderate the relationship between gender and the amount funded during the precampaign phase of prosocial crowdfunding, but this effect is weaker compared to vulnerability-framed MFIs listed exclusively on Kiva.*

3.2.2 | Rural Funding Bias and the Role of Vulnerability-Framed MFIs

In many developing economies, rural areas concentrate the highest levels of severe poverty, largely due to income instability, seasonal agricultural cycles and vulnerability to natural disasters such as droughts and floods (Mersland and Strøm 2010), agriculture is commonly perceived as a high-risk and low-return

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sector (Hishigsuren 2007), and the limited business skills among rural entrepreneurs may lead MFIs to prioritise financial sustainability over social objectives—ultimately reducing the allocation of credit to rural portfolios.

Cull et al. (2018) show that the number of the poorest clients served by MFIs has declined for the third consecutive year, suggesting that many MFIs focus their outreach on those near the poverty line rather than the extremely poor—an indication of *mission drift*. The high fixed costs associated with small loans, combined with the logistical challenges of serving remote areas, negatively affect MFI profitability. This contributes to a preference for urban clients engaged in high-turnover activities such as retail, as opposed to those involved in agriculture (Simanowitz 2011).

In this context, prosocial crowdfunding can play a vital role in bridging funding gaps by overcoming geographical constraints—even within traditional microfinance frameworks targeting underserved rural populations (e.g., the Grameen Bank). Agriculture remains the dominant sector in campaigns funded through Kiva (Kiva 2018, 2019), and Lendwithcare similarly reports high demand for farming-related loans (CARE 2019). This focus suggests that prosocial crowdfunding platforms are well-positioned to expand the traditional microcredit model and promote financial inclusion in rural areas.

Kiva pursues a social mission aimed at connecting vulnerable populations with credit to help them escape poverty (Kiva 2020). In a competitive environment where MFIs face increasing pressure to secure subsidies (Cull et al. 2009), clearly communicating their social mission becomes essential. As Kiva partners, MFIs express their commitment to disadvantaged rural entrepreneurs. During the pre-campaign phase, MFIs disburse loans to rural borrowers before these loans are posted on Kiva. Crowdfunding lenders effectively act as a form of post-disbursement insurance, covering loans already issued—without receiving interest. If an MFI fails to recover a loan, lenders may not be reimbursed, which could reduce their willingness to fund future projects and ultimately undermine the refinancing capacity of MFIs (Allison et al. 2013; Dorfleitner et al. 2020). As a result, framing plays a critical role in encouraging prosocial lending behaviour.

This framing is evident in the way borrower profiles are presented (Defazio et al. 2021; Jenq et al. 2015). In online platforms, portraying rural borrowers' vulnerability and illustrating how small loans enable them to initiate or expand income-generating activities increases the effectiveness of the campaign by aligning with lenders' expectations. For example, a typical rural loan profile reads:

> Sokkhai, 37, is married and has two school-aged children who live in a village in the Kratie Province of Cambodia. She and her husband have been working at a cashew farm for the past 17 years, typically earning around $10 per day. She is now requesting a loan as part of a group of three members. As the group leader (standing at the right of the picture), she will use her portion of the loan to grow more cashew. She believes this loan will allow her to increase crop yields and, ultimately, her income.

Such narratives employ motivational framing, combining descriptive vulnerability with aspirational outcomes. This framing not only portrays need in an accurate and humanising manner but also reinforces principles of fairness and inclusion, thereby increasing the likelihood of successful fundraising. We therefore argue that vulnerability-framed MFIs can strengthen funding outcomes for rural borrowers by constructing narratives that highlight their socio-economic challenges and the transformative potential of small-scale credit. This approach demonstrates fairness and inclusiveness, thereby increasing the likelihood of financing success. Therefore, we postulate that:

H2. *Vulnerability-framed MFIs positively moderate the relationship between rural settings and the amount funded during the pre-campaign phase of prosocial crowdfunding.*

H2a. *Vulnerability-framed MFIs that are exclusively listed on Kiva positively moderate the relationship between rural settings and the amount funded during the pre-campaign phase of prosocial crowdfunding.*

H2b. *Vulnerability-framed MFIs that are also listed on Mix Market positively moderate the relationship between rural settings and the amount funded during the pre-campaign phase of prosocial crowdfunding; however, this effect is weaker compared to vulnerability-framed MFIs listed exclusively on Kiva.*

3.2.3 | Group Lending Funding Bias and the Role of Vulnerability-Framed MFIs

Prior studies provide compelling evidence that narratives framing borrowers as belonging to disadvantaged groups enhance the perceived social value of campaigns, thereby increasing their likelihood of success (e.g., Defazio et al. 2021; Figueroa-Armijos and Berns 2022). However, little is known about how vulnerability-framed MFIs allocate capital between individual and group loan campaigns, particularly during the pre-campaign phase.

On Kiva, group loans are clearly distinguishable through several visual and textual cues. These include the explicit number of borrowers indicated on the loan page, group photographs and the use of collective names rather than individual identifiers. The profile descriptions invariably reference the collective nature of the loan and often highlight group dynamics and mutual accountability.

Group lending represents a key innovation in microfinance, popularised by the Grameen Model in Bangladesh and later adopted in the Self-Help Group (SHG) model in India. This approach was designed to harness the informational advantages of peer monitoring (Haldar and Stiglitz 2016), as first described by Stiglitz (1990), and to mitigate adverse selection problems (Ghatak 2000). Group lending mechanisms rely on joint liability, wherein members mutually guarantee loan repayment, reducing MFIs' risk exposure (Ghatak 1999; Morduch 1999) and lowering reliance on collateral as a screening and enforcement tool.

By leveraging peer selection and group discipline, group lending has historically been associated with lower default rates and

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higher repayment performance (Dorfleitner and Oswald 2016; Zhou and Wei 2020). Furthermore, the peer pressure and social capital embedded in group lending may encourage borrowers who would otherwise self-exclude—due to limited resources, collateral, financial literacy, or confidence—to apply for a loan. Thus, group lending is regarded as an inclusive financing mechanism capable of reaching the most vulnerable and excluded populations.

Yet, despite its potential, little is known about how MFIs behave during the pre-campaign phase—specifically how they frame and select individual versus group loans for funding via prosocial platforms like Kiva.

The microfinance literature offers mixed perspectives. Some studies point to a growing preference for individual loans due to their operational simplicity and greater scalability (Ahlin and Suandi 2019; De Quidt et al. 2018), while others stress the financial and social merits of group lending (Kodongo and Kendi 2013). From the perspective of framing theory, prosocial lenders are more likely to be influenced by emotionally resonant narratives that foster empathy and personal connection (Allison et al. 2013). As a result, individual loan campaigns tend to attract more funding than group loans, a dynamic explained by the identifiable victim effect—the tendency for donors to respond more strongly to individual stories than to collective ones (Galak et al. 2011).

Data from the Kiva platform further illustrates this bias. The average loan size across all partners is $404, but varies significantly between lending structures: individual loans average $603, whereas group loans average $1934 and typically involve 8.3 borrowers (Kiva 2024). Research by Ly and Mason (2012b) and Berns et al. (2021) also highlights that group loans are generally less popular among lenders, possibly due to the weaker emotional appeal of collective narratives. Since crowdfunding is strongly driven by storytelling, the less personalised nature of group loan campaigns may result in a funding disadvantage.

This disadvantage may be exacerbated when vulnerability-framed MFIs act as intermediaries. Their institutional identity may lead them to prioritise individual borrowers who can be portrayed as visibly vulnerable, rather than groups who may appear more organised or self-sufficient (Hogg and Terry 2014).

However, group lending also serves as a mechanism to support individuals who lack the confidence or capacity to access finance independently. Given that MFIs with a strong prosocial orientation may more closely identify with marginalised borrower groups (Tajfel and Turner 1979), they may attempt to counteract lender biases against group loans.

By framing group lending as a collective strategy that empowers the vulnerable through shared responsibility and social capital, vulnerability-framed MFIs may help close the funding gap for group borrowers during the pre-campaign stage. Empirical evidence supports this possibility. Dorfleitner et al. (2021) show that effective framing can increase the attractiveness of group lending campaigns. Similarly, Figueroa-Armijos and Berns (2022) demonstrate that prosocial lenders are more likely to support campaigns aligned with broader social impact narratives, not just individual appeals.

On the one hand, vulnerability-framed MFIs may favour individual loans to maximise their fundraising performance. On the other hand, their social mission may lead them to frame and prioritise group lending as a tool for financial inclusion. In the context of prosocial crowdfunding, we argue that MFIs' framing strategies—whether favouring individual or group loans—are shaped by their institutional focus and funding model. Specifically, vulnerability-framed MFIs exclusively listed on Kiva, which are more dependent on Kiva's zero-interest capital, are likely to emphasise group lending campaigns framed as mechanisms for empowering vulnerable populations through collective responsibility. In contrast, MFIs also listed on Mix Market, which enjoy access to alternative funding sources (e.g., government grants, deposits), may rely less on Kiva and thus focus more on individual loans that appeal to empathy and emotional connection—resulting in faster fundraising outcomes. Thus, we formulate:

H3. *Vulnerability-framed MFIs positively moderate the relationship between group loans and the amount funded during the pre-campaign phase of prosocial crowdfunding.*

H3a. *Vulnerability-framed MFIs that are exclusively listed on Kiva positively moderate the relationship between group loans and the amount funded during the pre-campaign phase of prosocial crowdfunding.*

H3b. *Vulnerability-framed MFIs that are also listed on Mix Market positively moderate the relationship between group loans and the amount funded in the pre-campaign phase of prosocial* crowdfunding; *however, this effect is weaker compared to vulnerability-framed MFIs listed exclusively on Kiva.*

4 | Research Design

4.1 | Data Source

We collected data from the prosocial crowdfunding platform Kiva. Founded in the United States as a nonprofit organisation, Kiva hosts the world's largest publicly accessible database of microentrepreneur campaigns (Kiva 2021a). Its core mission is to expand financial access to underserved communities. Because a significant platform redesign introduced notable changes in content and structure,[6] we restricted our sample to loans posted between 2017 and 2018. This period provides a consistent and transparent window into pre-campaign institutional behaviour, allowing us to analyse MFIs' framing activities before campaigns become visible to lenders. During this period, the platform facilitated the raising and disbursement of approximately US$310 million in loans, equivalent to nearly US$300 per minute (Kiva 2018, 2019).

4.2 | Population and Sample

The initial dataset comprises 442,842 intermediary-based loans backed by MFIs. To ensure consistency and data

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reliability, we applied several exclusion criteria. First, we removed 21,234 loans associated with MFIs that were no longer active on Kiva at the time of data collection. Second, we excluded 4806 loans linked to MFIs with ratings outside the conventional 1–5 scale, in line with industry standards for MFI evaluation (Jancenelle et al. 2019). In addition, we focused exclusively on business loans, consistent with the view that microfinance-supported entrepreneurship contributes to poverty alleviation through the promotion of income-generating activities. Accordingly, 59,655 non-business loans were excluded from the analysis. To ensure completeness across the dataset, we also excluded 22,295 loans with missing values in any variable used in our empirical models. These filtering procedures resulted in a final sample of 334,852 microloans issued by 140 distinct MFIs operating across 59 countries. See Table 1.

In terms of temporal distribution, 47.71% of the campaigns in the sample were launched in 2017, with the remaining 52.29% launched in 2018. Regarding the economic classification of the countries involved, 61.42% of the loans originated in lower-middle-income countries, 20.39% in low-income countries and 18.17% in upper-middle-income countries. A negligible proportion (0.03%) originated from high-income countries. Geographically, the sample includes 59 countries, with the Philippines and Kenya accounting for the largest shares of loans—25.00% and 13.96%, respectively. By contrast, countries such as Panama (0.005%), the United States (0.01%), Israel (0.02%), Thailand (0.003%), Indonesia (0.04%) and Georgia (0.07%) represent only a marginal portion of the sample, each contributing less than 0.10%.

With respect to institutional representation, 97 of the 140 MFIs in the final sample (69.3%) are also listed on the Mix Market platform (see Table A1 in Supporting Information). These MFIs account for 90% of the total number of loans in the dataset, amounting to 301,664 loans. Among these institutions, the Negros Women for Tomorrow Foundation (NWTF), which is listed on Mix Market, stands out as the most active MFI, representing 18.96% of all campaigns launched during the 2017–2018 period.

4.3 | Variables

The dependent variable used in this study is the Normalized APreF, which represents the loan amount (in US dollars) prefunded by the MFI during the pre-campaign phase. For group loans, this value is averaged per borrower. To account for cross-country economic disparities, this amount is normalised using the ratio between each country's GDP per capita (GDPpc) in purchasing power parity (PPP) terms and the GDPpc of the United States.[7]

The main independent variables capture both the vulnerability-framed orientation of MFIs and the characteristics of vulnerable borrower groups. The variable Vulnerability-framed MFI is a binary indicator denoting whether the lending institution holds the 'Anti-poverty' and/or 'Vulnerability' social badge assigned by Kiva. This measure reflects the extent to which an MFI is institutionally oriented toward serving vulnerable populations through prosocial framing strategies. The variable Female is also binary and indicates whether the borrower is a woman or belongs to a women-majority group, thereby capturing gender-specific dynamics in funding outcomes. The variable Rural identifies loans directed toward the agricultural sector, serving as a proxy for borrowers located in rural or economically marginalised areas. Finally, Group Loans is a binary variable that distinguishes between loans requested by multiple borrowers and those associated with individual applicants.

To control for potential confounding factors, we include both loan-specific and MFI-specific variables. Loan characteristics include Maturity (measured in months), the number of Words used in the loan description, and the Repayment structure (monthly or otherwise).[8] On the institutional side, we account for the Default Rate reported by each MFI, the Kiva-assigned Rating (on a scale from 1 to 5), the Mix Market listed status, and the Country GDPpc, reflecting broader macroeconomic conditions. All these variables were selected to capture both borrower-level heterogeneity and institutional differences, ensuring that our multilevel model specification accounts for all theoretically relevant sources of variation identified in the literature.

A comprehensive description of all variables is provided in Table 2.

4.4 | Descriptive Statistics

Table 3 presents the descriptive statistics for the full sample. The average loan amount prefunded during the pre-campaign phase is $507.784, with a maximum of $9825. When normalised by GDP per capita in PPP terms, the average value increases substantially to $5508.429, with significant cross-country variability and a maximum of $425,121.20. Disaggregating by MFI type reveals that MFIs also listed on Mix Market exhibit a considerably higher average normalised prefunding amount ($5718.749) compared to those only listed on Kiva ($3596.713). To address skewness in the distribution, we apply a logarithmic transformation to the normalised dependent variable in our regression models.

In terms of borrower characteristics, female borrowers represent 79.9% of the overall sample. Among MFIs, those also listed on Mix Market report a higher proportion of female-targeted loans (81.8%) than MFIs only listed on Kiva (62.7%). With respect to rural loans—identified through agricultural sector lending—18.2% of all loans fall into this category. However, this figure diverges substantially by MFI type: MFIs only listed on Kiva allocate 47.3% of their loans to rural borrowers, whereas MFIs listed on Mix Market allocate just 15%. As for group loans, these constitute 13.6% of the sample, with a notable disparity: 24.9% of loans from MFIs listed only on Kiva are group loans, compared to just 12.3% for MFIs listed on Mix Market.

These statistics suggest that MFIs listed on Mix Market are more inclined to target women, likely due to the higher social returns associated with gender-based lending, which are valued by Kiva investors. However, these MFIs also appear more risk-averse, avoiding rural borrowers and group lending structures, both of which may involve higher operational complexity or credit risk.

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TABLE 1 | Sample characteristics.

Panel A. Year			Panel B. Country income level		
Year	Frequency	Percent	MFI country income	Frequency	Percent
2017	159,748	47.71	High income	93	0.03
2018	175,104	52.29	Upper middle income	60,832	18.17
Total	334,852	100	Lower middle income	205,663	61.42
			Low income	68,264	20.39
			Total	334,852	100

Panel C. Country list

	MFI country	# Loans	Percent		MFI country	# Loans	Percent
1	Albania	460	0.14	31	Moldova	340	0.10
2	Armenia	2826	0.84	32	Mozambique	1062	0.32
3	Bolivia	2909	0.87	33	Myanmar	2563	0.77
4	Brazil	617	0.18	34	Nepal	426	0.13
5	Burkina Faso	1717	0.51	35	Nicaragua	4956	1.48
6	Cambodia	5293	1.58	36	Nigeria	4133	1.23
7	Cameroon	1554	0.46	37	Pakistan	9038	2.70
8	Colombia	16,856	5.03	38	Panama	16	0.00
9	Costa Rica	704	0.21	39	Paraguay	5711	1.71
10	DR Congo	1518	0.45	40	Peru	10,693	3.19
11	Dominican Republic	419	0.13	41	Philippines	83,702	25.00
12	Ecuador	11,364	3.39	42	Rwanda	2845	0.85
13	Egypt	2272	0.68	43	Samoa	5521	1.65
14	El Salvador	18,397	5.49	44	Senegal	1818	0.54
15	Fiji	1163	0.35	45	Sierra Leone	4069	1.22
16	Georgia	222	0.07	46	Solomon Islands	1013	0.30
17	Ghana	3342	1.00	47	Tajikistan	9734	2.91
18	Guatemala	3158	0.94	48	Tanzania	5696	1.70
19	Honduras	4194	1.25	49	Thailand	85	0.03
20	Indonesia	122	0.04	50	Timor-Leste	2085	0.62
21	Israel	69	0.02	51	Togo	4481	1.34
22	Jordan	2184	0.65	52	Tonga	564	0.17
23	Kenya	46,741	13.96	53	Turkey	1073	0.32
24	Kosovo	502	0.15	54	Uganda	15,428	4.61
25	Lebanon	3824	1.14	55	United States	17	0.01
26	Liberia	4633	1.38	56	Vietnam	4658	1.39
27	Madagascar	5398	1.61	57	West Bank and Gaza	2866	0.86
28	Malawi	1135	0.34	58	Zambia	827	0.25
29	Mali	1060	0.32	59	Zimbabwe	3894	1.16
30	Mexico	885	0.26				
					Total	334,852	100

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TABLE 2 | Variables definition.

Variables	Measure	Definition
Dependent		
Amount prefunded	US dollars	Loan amount prefunded (US dollars) by the MFI in the precampaign phase (average amount by borrower).
Normalized APreF	US dollars	Loan amount prefunded (US dollars) normalised by GDPpc and PPP differences (= Amount Prefunded/(GDPpcPPP Country/GDPpcPPP in USA)).
Independent		
Vulnerable groups		
Female	Binary	1 if the individual borrower is a female or if women-majority groups, 0 otherwise.
Rural	Binary	1 if loan is from agriculture sector, and 0 if loan is from other sectors.
Group loans	Binary	1 if the loan campaign is promoted by more than one borrower, and 0 if is a single loan campaign.
MFI orientation		
Vulnerability framed	Binary	1 if the MFI has the social badge 'Anti-poverty focus' and/or 'Vulnerable group focus assigned by Kiva', and 0 otherwise.
Controls		
Loan characteristics		
Maturity	Months	Loan maturity in months.
Words	Discrete	Number of words used in the descriptive text to describe the loan purpose.
Repayment	Binary	1 if the repayment instalments of loan are made in a monthly basis, and 0 otherwise.
MFI characteristics		
Default rate	%	Amount of loans defaulted, divided by amount of total loans.
Rating	Continuous	MFI rating assigned by Kiva, ranging from 1 (high risk) to 5 (low risk).
MIX market listed	Binary	1 if the MFI is also listed on Mixed Market, 0 otherwise.
Country GDPpc	US dollars	Gross Domestic Product per capita (GDPpc) in PPP (Constant Prices)

Regarding institutional orientation, 74.6% of loans in the dataset are issued by MFIs identified as vulnerability-framed. This proportion is virtually identical across the two MFI types: 74.6% among those also listed on Mix Market and 75% among those only listed on Kiva. This consistency offers a valuable setting in which to examine the role of vulnerability framing in the prefunding of loans.

Loan structure indicators reveal that the average loan maturity is 12.47 months, and 86.8% of loans follow a monthly repayment schedule. MFIs listed exclusively on Kiva tend to offer more borrower-friendly terms, with an average loan maturity of 13.902 months and a significantly lower incidence of monthly repayment (51.9%) compared to MFIs listed on Mix Market, which report an average maturity of 12.317 months and a monthly repayment rate of 90.6%. These patterns suggest that Kiva-only MFIs may adopt more flexible and socially oriented repayment structures.

The average default rate across all MFIs is 0.948%, and the average Kiva rating is 3.325 (on a scale from 1 to 5). MFIs also listed on Mix Market demonstrate stronger performance, with a lower average default rate (0.923%) and a higher rating (3.363) compared to MFIs listed only on Kiva, which report a higher default rate (1.175%) and a lower average rating (2.984).[9]

Table 4 reports the pairwise correlations between all dependent and independent variables, as well as the Variance Inflation Factor (VIF) statistics for the full sample. Correlation coefficients are low to moderate, and all VIF values are below the conventional threshold of 5, indicating that multicollinearity is not a concern in the regression analysis.

4.5 | Model Specification

To analyse MFIs' precampaign funding behaviour—measured as the log-transformed normalised amount prefunded—we employ a multilevel random effects (MLRE) model. This method is particularly suitable for hierarchical data structures, such as those observed in crowdfunding contexts, where loans (Level 1) are nested within MFIs (Level 2) (e.g., Anglin et al. 2020). The multilevel framework enables us to simultaneously account for variability at both the loan and

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TABLE 3 | Descriptive statistics.

		Panel A. Full sample					Panel B. Subsample					
							B.1. MFIs also listed on mix market			B.2. MFIs only listed on Kiva		
Variables	**Measure**	**# Loans**	**Mean**	**Std. dev.**	**Min**	**Max**	**# Loans**	**Mean**	**Std. dev.**	**# Loans**	**Mean**	**Std. dev.**
Dependent												
Amount Prefunded (APreF)	US dollars	334,852	507.784	440.14	0	9825	301,664	522.713	431.042	33,188	372.081	495.312
Normalized APreF	US dollars	334,852	5508.429	6193.823	0	42,5121.2	301,664	5718.749	6145.783	33,188	3596.713	6300.489
ln(Normalized APreF +1)	ln form	334,852	7.996	1.728	0	12.96	301,664	8.258	1.031	33,188	5.617	3.768
Independent												
Loan campaign orientation												
Female	Binary	334,852	0.79	0.401	0	1	301,664	0.818	0.386	33,188	0.627	0.484
Rural	Binary	334,852	0.182	0.385	0	1	301,664	0.150	0.357	33,188	0.473	0.499
Group loans	Binary	334,852	0.136	0.342	0	1	301,664	0.123	0.329	33,188	0.249	0.432
MFI orientation												
Vulnerability	Binary	334,852	0.746	0.435	0	1	301,664	0.746	0.436	33,188	0.750	0.433
Controls												
Loan characteristics												
Maturity	Months	334,852	12.474	5.346	2	98	301,664	12.317	5.376	33,188	13.902	4.841
ln(Maturity)	ln form	334,852	2.447	0.384	0.693	4.585	301,664	2.432	0.388	33,188	2.581	0.316
Words	Number	334,852	118.766	42.953	4	369	301,664	117.269	42.709	33,188	132.38	42.771
ln(Words)	ln form	334,852	4.716	0.346	1.386	5.911	301,664	4.704	0.344	33,188	4.829	0.348
Repayment	Binary	334,852	0.868	0.339	0	1	301,664	0.906	0.292	33,188	0.519	0.5

(Continues)

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TABLE 3 | (Continued)

Variables	Measure	Panel A. Full sample					Panel B. Subsample					
							B.1. MFIs also listed on mix market			B.2. MFIs only listed on Kiva		
		# Loans	Mean	Std. dev.	Min	Max	# Loans	Mean	Std. dev.	# Loans	Mean	Std. dev.
MFI characteristics												
Default rate	%	334,852	0.948	1.811	0	14.63	301,664	0.923	1.739	33,188	1.175	2.356
Rating	Continuous	334,852	3.325	0.983	1	4.5	301,664	3.363	0.973	33,188	2.984	1.002
MIX market listed	Binary	334,852	0.901	0.299	0	1	301,664	1	0	33,188	0	0
Country GDPpc	US dollars	334,852	7226.83	4236.922	930.528	62641.01	301,664	7252.613	4220.602	33,188	6992.468	4375.577
ln(Country GDPpc)	ln form	334,852	8.687	0.673	6.836	11.045	301,664	8.689	0.68	33,188	8.673	0.601

institutional levels, while controlling for unobserved heterogeneity across MFIs.

Following the notation of Raudenbush and Bryk′ (2002), the model is specified as follows:

$$\begin{aligned}\ln(\text{Normalized APreF}_{ij}+1) = {} & \gamma_0+\gamma_1\text{Female}_{ij}+\gamma_2\text{Rural}_{ij}+\gamma_3\text{GroupLoan}_{ij}\\ & +\gamma_4\text{Vulnerability framed}_j\\ & +\gamma_5(\text{Vulnerability framed}_j\times\text{Female}_{ij})\\ & +\gamma_6(\text{Vulnerability framed}_j\times\text{Rural}_{ij})\\ & +\gamma_7(\text{Vulnerability framed}_j\times\text{Group}_{ij})\\ & +\sum_{k=1}^{3}\phi_k X_{kij}+\sum_{w=1}^{4}\lambda_w Z_{wj}+\mu_{0j}+\varepsilon_{ij},\end{aligned} \tag{1}$$

where APreF_{ij} represents the amount prefunded by loan i within MFIj. Female_{ij}, Rural_{ij}, GroupLoan_{ij} and the vector X_{kij} include covariate loan controls—that is, maturity, number of words and repayment structure—are Level-1 variables, varying across individual loans i within MFIj. MFI Vulnerability-framed$_j$, and the vector Z_{wj} include covariate MFI-level characteristic controls—that is, default rate, rating, Mix Market status and MFI's country GDP per capita—are Level-2 variables, varying between MFIs but constant within each MFI. μ_{0j} is the random intercept, capturing unobserved heterogeneity at the MFI level, and ε_{ij} is the idiosyncratic error term at the loan level.

This baseline model, which includes key interactions between MFI vulnerability orientation and borrower characteristics (gender, rural location and group structure), is designed to test the main research hypotheses H1, H2 and H3. Specifically, the interaction terms allow us to examine whether vulnerability-framed MFIs behave differently when funding female borrowers, rural borrowers, or group loans. To test the sub-hypotheses H1a–H1b, H2a–H2b and H3a–H3b, we estimate the model using subsamples, distinguishing between MFIs that are only listed on Kiva and those that are also listed on Mix Market. This approach allows us to assess whether the moderating role of vulnerability framing varies depending on the institutional funding environment and access to alternative sources of capital.

4.6 | Model Assumptions and Validity Checks

Our MLRE modelling approach assumes that μ_{0j} and ε_{ij} are normally distributed, and that the random part of the model is uncorrelated with the regressors. Violations of the random effects assumption may lead to biased estimates due to endogeneity. To validate this assumption, we follow Antonakis et al. (2021) by estimating a Correlated Random Effects (CRE) model, which incorporates the cluster mean of the Level-1 covariates. If the coefficients of these cluster means are not statistically significant, the random-effects assumption holds, thereby confirming the consistency of the MLRE estimates.

Table A2, in the Supporting Information, shows the results of the ordinary least squares (OLS) (Column I), the MLRE model (Column II) and the CRE model (Columns III.1–3).[10] The coefficients of the cluster means are not statistically significant in any of the CRE estimations (Columns III.1–III.3;

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TABLE 4 | Pairwise correlation matrix and variance inflation factors (VIF) (full sample).

Variables	VIF		1	2	3	4	5	6	7	8	9	10	11	12
Dependent														
ln(Normalized APreF +1)		1	1											
Independent														
Vulnerable groups														
Female	1.16	2	0.040*	1										
Agriculture	1.32	3	−0.217*	−0.195*	1									
Group loans	1.26	4	−0.196*	0.062*	0.099*	1								
MFI orientation														
Vulnerability framed	1.10	5	−0.082*	0.118*	−0.010*	−0.018*	1							
Controls														
Loan characteristics														
ln(Maturity)	1.24	6	0.116*	−0.205*	0.160*	−0.249*	−0.113*	1						
Repayment	1.47	7	−0.101*	−0.058*	0.257*	0.197*	−0.033*	0.148*	1					
ln(Words)	1.20	8	0.321*	0.239*	−0.421*	−0.253*	0.076*	−0.111*	−0.189*	1				
MFI characteristic														
Default rate	1.23	9	−0.127*	−0.197*	0.071*	−0.076*	0.011*	0.250*	0.187*	−0.153*	1			
Rating	1.37	10	−0.082*	0.116*	0.005*	−0.108*	0.232*	−0.055*	−0.091*	0.010*	−0.126*	1		
MIX market listed	1.19	11	0.457*	0.143*	−0.251*	−0.109*	−0.003*	−0.115*	−0.108*	0.341*	−0.042*	0.115*	1	
ln(Country GDPpc)	1.31	12	−0.180*	−0.010*	−0.088*	−0.123*	0.035*	0.025*	−0.164*	0.010*	0.148*	0.394*	0.007*	1

*$p < 0.05$.

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$p > 0.1$), supporting the validity of the random effects assumption. Moreover, the likelihood ratio test reveals no significant difference between the MLRE and CRE estimations ($p > 0.1$), further confirming that the MLRE specification is appropriate. This conclusion is reinforced by an additional likelihood ratio test comparing the OLS and MLRE models, which rejects the null hypothesis that the two approaches yield equivalent estimates ($\chi^2 = 206{,}025.84$, $p < 0.01$). These results strongly support the use of the multilevel modelling framework in our analysis.

5 | Results

5.1 | Baseline Findings

Table 5 reports the results of the multilevel estimations based on Equation (1), accounting for borrower/loan (Level 1) and MFI (Level 2) characteristics. Columns AI.1 to AI.3 present the partial models, while Column A.II shows the full model for the global sample. Columns B.1 and B.2 display the results for the two subsamples: MFIs also listed on Mix Market (B.1) and MFIs only listed on Kiva (Column B.2). For brevity, the discussion focuses on the full models (Columns AII, B.1 and B.2).

Baseline results show that MFIs not framed as an MFI vulnerability-oriented systematically exhibit a funding disadvantage across all types of vulnerable borrowers (p value < 0.01). This pattern is consistent for female (A.II: $\gamma_{\text{Female}} = -0.095$), rural ($\gamma_{\text{Rural}} = -0.118$) and group borrowers ($\gamma_{\text{Group}} = -0.486$). These patterns hold across both types of MFIs—those listed on Mix Market (B.1: $\gamma_{\text{Female}} = -0.072$; $\gamma_{\text{Rural}} = -0.108$; $\gamma_{\text{Group}} = -0.445$) and those only listed on Kiva (B.2: $\gamma_{\text{Female}} = -0.159$; $\gamma_{\text{Rural}} = -0.244$; $\gamma_{\text{Group}} = -1.710$). In addition, a significant funding gap is observed for rural borrowers, especially among MFIs only listed on Kiva.

With respect to MFIs framed around vulnerability, the results indicate a strong positive effect on the amount prefunded (A.II: $\gamma_{\text{Vulnerability}} = 0.991$; p value < 0.05). Although both MFI groups display similar proportions of vulnerability framing—74.6% for Mix Market MFIs and 75% for Kiva-only MFIs (Table 3, Panel B)—the impact of this framing differs substantially. For MFIs only listed on Kiva, the effect of the vulnerability badge is particularly pronounced (B.2: $\gamma_{\text{Vulnerability}} = 2.876$; p value < 0.05), whereas for those also listed on Mix Market, the effect is modest (B.1: $\gamma_{\text{Vulnerability}} = 0.429$; p value < 0.10). This suggests that MFIs with access to broader funding channels may place less emphasis on prosocial framing.

Regarding gender, the interaction term between vulnerability framing and female borrowers is positive and significant across all models (A.II: $\gamma_{\text{Vulnerability}\times\text{Female}} = 0.075$; p value < 0.01; B.1: $\gamma_{\text{Vulnerability}\times\text{Female}} = 0.017$; p value < 0.10; B.2: $\gamma_{\text{Vulnerability}\times\text{Female}} = 0.297$; p value < 0.05), indicating that vulnerability-framed MFIs mitigate the gender funding gap. Notably, only MFIs listed solely on Kiva fully offset the disadvantage for women, as the combined effect is positive (B.2: $\gamma_{\text{Vulnerability}\times\text{Female}} + \gamma_{\text{Female}} > 0$). This suggests that Kiva-only MFIs, when strategically framing their mission around vulnerability, prioritise female borrowers during the pre-campaign phase, likely recognising the empowerment impact of lending to women in contexts where gender inequality persists. These findings confirm Hypothesis 1 and support both H1a and H1b.

Turning to rural borrowers, the baseline coefficients indicate a negative relationship with prefunding levels, which persists even among vulnerability-framed MFIs. However, the interaction term is positive and significant (A.II: $\gamma_{\text{Vulnerability}\times\text{Rural}} = 0.087$; p value < 0.01; B.1: $\gamma_{\text{Vulnerability}\times\text{Rural}} = 0.077$; p value < 0.01; B.2: $\gamma_{\text{Vulnerability}\times\text{Rural}} = 0.157$; p value < 0.10) suggesting that vulnerability-framed MFIs do help reduce—but not eliminate—the funding gap for rural campaigns ($\gamma_{\text{Rural}} + \gamma_{\text{VulnerabilityxRural}} < 0$). These results support Hypothesis 2, as well as H2a and H2b, but also highlight the persistence of structural disadvantages in rural microfinance access.

Group loans show a pronounced funding disadvantage relative to individual loans, as evidenced by the consistently negative baseline coefficients (p value < 0.01) across all specifications (A.II: $\gamma_{\text{Group}} = -0.486$; B.1: $\gamma_{\text{Group}} = -0.445$; B.2: $\gamma_{\text{Group}} = -1.710$). This pattern suggests a structural preference for individual lending models, even in prosocial crowdfunding contexts. The interaction effects provide a more nuanced picture of how MFIs' vulnerability framing shapes this bias. In the full sample, the interaction between the vulnerability badge and group loans is significantly negative (A.II: $\gamma_{\text{VulnerabilityxGroup}} = -0.174$; p value < 0.01), indicating that vulnerability framing does not mitigate—and may even reinforce—the baseline disadvantage faced by group borrowers. A similar pattern emerges among MFIs listed on Mix Market (B.1: $\gamma_{\text{Vulnerability}\times\text{Group}} = -0.188$; p value < 0.01) pointing to a potential tension between social branding and commercially oriented funding preferences. These findings are inconsistent with H3b, which anticipated a positive moderating effect in this subgroup. In contrast, results from MFIs listed exclusively on Kiva reveal a distinct pattern. The interaction between vulnerability framing and group loans is strongly positive and significant (B.2: $\gamma_{\text{Vulnerability}\times\text{Group}} = +1.991$, $p < 0.01$), more than offsetting the baseline disadvantage ('net effect' $= -1.710 + 1.991 = +0.281$). This suggests that these MFIs, which rely solely on Kiva's zero-interest capital, actively frame group loan campaigns as vehicles for promoting financial inclusion, particularly among borrowers who may lack the confidence or capacity to seek credit individually. In these settings, vulnerability framing appears to serve its intended purpose—empowering marginalised groups through collective responsibility. Together, these results partially support Hypothesis 3. While H3a is confirmed, as vulnerability-framed MFIs exclusively on Kiva effectively reverse the group lending disadvantage, H3b is not supported, given the absence of a positive moderating effect among MFIs also listed on Mix Market.

These findings highlight that MFIs' vulnerability framing positively moderates the relationship between vulnerable borrowers (female, rural and group) and the prefunded amount granted in the precampaign phase. However, this positive effect is maximised when MFIs rely solely on Kiva's zero-subsidised debt, indicating a trade-off between reaching vulnerable groups and maintaining financial sustainability. Section 6 provides a detailed discussion of these findings.

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TABLE 5 | Multilevel estimations.

Panel A. Full sample	Partial models			Full model
	A.I.1	A.I.2	A.I.3	A.II
Independent				
First level—Loan				
Female	−0.081***	−0.045***	−0.044***	−0.095***
	(0.009)	(0.005)	(0.005)	(0.009)
Rural	−0.058***	−0.108***	−0.057***	−0.118***
	(0.006)	(0.011)	(0.006)	(0.011)
Group loan	−0.598***	−0.599***	−0.496***	−0.486***
	(0.011)	(0.011)	(0.019)	(0.019)
Second Level—MFI				
Vulnerability framed	0.987**	1.016**	1.062**	0.991**
	(0.419)	(0.419)	(0.419)	(0.419)
Interactions				
Vulnerability Framed × female	0.058***			0.075***
	(0.011)			(0.011)
Vulnerability Framed × rural		0.074***		0.087***
		(0.013)		(0.013)
Vulnerability Framed × group loan			−0.159***	−0.174***
			(0.023)	(0.023)
Controls				
First level—Loan				
ln(Maturity)	0.680***	0.678***	0.679***	0.678***
	(0.008)	(0.008)	(0.008)	(0.008)
ln(Words)	0.144***	0.145***	0.148***	0.148***
	(0.009)	(0.009)	(0.009)	(0.009)
Repayment	−0.056***	−0.064***	−0.057***	−0.061***
	(0.008)	(0.008)	(0.008)	(0.008)
Second level—MFI				
Default rate	−0.058	−0.057	−0.059	−0.059
	(0.081)	(0.081)	(0.081)	(0.081)
Rating	0.074	0.073	0.074	0.073
	(0.206)	(0.206)	(0.206)	(0.206)
MIX market listed	3.189***	3.191***	3.184***	3.185***
	(0.466)	(0.467)	(0.466)	(0.466)
ln(Country GDPpc)	−0.606**	−0.607**	−0.608**	−0.607**
	(0.246)	(0.246)	(0.246)	(0.246)

(Continues)

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Panel A. Full sample				
	Partial models			**Full model**
	A.I.1	**A.I.2**	**A.I.3**	**A.II**
Fixed effect (year)	Included	Included	Included	Included
Intercept	7.422***	7.422***	7.381***	7.434***
	(2.161)	(2.161)	(2.160)	(2.160)
Observations	334,852	334,852	334,852	334,852
Number groups (MFI)	140	140	140	140
Random-effects parameters				
Individual-level variance	1.053	1.053	1.054	1.052
	(0.003)	(0.003)	(0.003)	(0.003)
MFI-level variance	5.433	5.437	5.428	5.431
	(0.657)	(0.658)	(0.657)	(0.657)
Model performance				
Log likelihood	−484,304.02	−484,301.27	−484,294.05	−484,253.75
Wald Chi^2	12,496.72***	12,502.37***	12,517.47***	12,601.02***
Likelihood ratio tests	[A.II vs. A.I.1]	[A.II vs. A.I.2]	[A.II vs. A.I.3]	
Chi^2	100.52***	95.04***	80.59***	

Panel B. Subsample		
	MFIs also listed on Mix Market	**MFIs only listed on Kiva**
	B.1	**B.2**
Independent		
First level—Loan		
Female	−0.072***	−0.159***
	(0.007)	(0.061)
Rural	−0.108***	−0.244***
	(0.009)	(0.072)
Group loan	−0.445***	−1.710***
	(0.014)	(0.182)
Second level—MFI		
Vulnerability framed	0.429*	2.876**
	(0.253)	(1.326)
Interactions		
Vulnerability framed × female	0.017*	0.297***
	(0.009)	(0.070)
Vulnerability framed × rural	0.077***	0.157*
	(0.010)	(0.094)
Vulnerability framed × group loan	−0.188***	1.991***
	(0.018)	(0.249)

(Continues)

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TABLE 5 | (Continued)

Panel B. Subsample	MFIs also listed on Mix Market	MFIs only listed on Kiva
	B.1	B.2
Controls		
First level—Loan		
ln(Maturity)	0.830***	−0.977***
	(0.006)	(0.059)
ln(Words)	0.077***	0.730***
	(0.007)	(0.068)
Repayment	−0.107***	0.430***
	(0.007)	(0.071)
Second level—MFI		
Default rate	−0.257***	0.105
	(0.075)	(0.167)
Rating	0.182	−0.740
	(0.123)	(0.695)
MIX market listed	—	—
ln(Country GDPpc)	−0.765***	0.245
	(0.159)	(0.698)
Fixed effect (year)	Included	Included
Intercept	12.180***	1.781
	(1.356)	(6.360)
Observations	301,664	33,188
Number groups (MFI)	97	43
Random-effects parameters		
Individual-level variance	0.584	5.116
	(0.002)	(0.040)
MFI-level variance	1.413	14.448
	(0.204)	(3.194)
Model performance		
Log likelihood	−347,412.76	−74,310.576
Wald Chi^2	27,302.81***	721.34***

Note: MLRE, Random Intercept. Dependent variable: ln(Normalized APreF +1). Second Level: MFI. ***$p<0.01$; **$p<0.05$; * $p<0.1$. Standard errors in parentheses.

5.2 | Robustness Check

5.2.1 | Reverse Causality

One critical issue that can compromise the validity of our results is simultaneity, or reverse causality, where the direction of the causal relationship between MFIs with a vulnerability focus and precampaign funding amounts might not be entirely clear. While we hypothesise that MFIs' vulnerability framing influences funding behaviours in the precampaign phase, the funding amounts approved during this phase could also affect how MFIs frame their institutional image. For instance, MFIs might adjust their funding priorities based on borrower characteristics that align with the platform's visibility or reputational incentives, such as the prosocial badges attributed by Kiva.

To address the issue of potential reverse causality (endogeneity), we employed an instrumental variable (IV) approach (Semadeni et al. 2014), specifically a two-stage residual inclusion (2SRI) estimation (Terza et al. 2008). The results of this analysis are

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presented in Supporting Information: Table A3. The instrument used in our analysis is the MFI Market Share, defined as the market share of the focal MFI's portfolio relative to funded loans on Kiva. The theoretical rationale for using this instrument is grounded in the premise that market share reflects an MFI's operational scope and competitive positioning, which influence its strategic focus on vulnerability but are unlikely to affect precampaign funding amounts directly. The effectiveness of the IV approach and the MFI Market Share as an instrument relies on two critical conditions: relevance and exogeneity (Kennedy 2008). Relevance requires that the instrument is strongly correlated with the endogenous variable, while exogeneity ensures the instrument's independence from the error term in the main equation.

In the first step, a logistic regression model was estimated to predict the likelihood of MFIs adopting a vulnerability focus (Panel A, Column I.1). This step establishes whether the instrument is relevant—that is, strongly correlated with the endogenous variable. The results confirm the relevance of the instrument, with the coefficient for ln(MFI Market Share+1) being positive and highly significant ($\gamma = 0.331$; $p < 0.01$). These findings confirm that the instrument satisfies the relevance criterion, as it is strongly associated with the endogenous variable (vulnerability focus).

In the second step, we implemented the Two-Stage Residual Inclusion (2SRI) method, where the residuals from the first stage are incorporated as an additional regressor in the second-stage model (Panel A, Column I.2). This method evaluates whether endogeneity biases the estimated relationship between MFIs' vulnerability-framed and precampaign funding amounts. Key results from this step include a coefficient for Vulnerability Residuals, which is not statistically significant ($\gamma = -1.873$; $p > 0.10$). This suggests that the endogenous component of the vulnerability focus does not significantly influence precampaign funding amounts, providing evidence against the presence of substantial endogeneity.

To further validate the exogeneity of the instruments, we estimated a simple OLS regression, including the instruments directly (Panel A, Column II). The goal was to confirm that the instruments do not directly affect the dependent variable (precampaign funding amounts) beyond their correlation with the endogenous variable. Findings show that the coefficient of Market Share is not statistically significant ($\gamma = 0.011$: $p > 0.1$), indicating that it does not directly influence precampaign funding amounts. The instrument's strength was further evaluated using the *F*-test (Stock and Yogo 2005) based on bootstrap resampling with 500 repetitions (Panel B). The observed F-statistics exceed the conventional threshold of 10 (Staiger and Stock 1994), indicating no weak instrument concerns. In conclusion, we find no indication that reverse causality is biasing our estimates.

5.2.2 | Sample Distribution

To address potential distortions caused by extreme values in prefunded amounts, we winsorised the data and truncated it at the 95th percentile. The high standard deviation relative to the Normalized APreF variable (Table 3, Panel A) reveals a right-skewed distribution, indicating that outliers could influence results even after applying a logarithmic transformation. Robustness checks reported in Supporting Information: Table A4 confirm that winsorising and truncating the data do not affect the direction or statistical significance of our main estimates. These results reinforce the robustness of our findings by demonstrating that they are not driven by extreme values.

5.2.3 | Over- and Under-Representation: Country and MFIs

To further ensure the generalizability of our results, we excluded observations from countries that are either heavily over-represented or under-represented in the sample. Specifically, we removed countries contributing more than 10% of total loans (Kenya and the Philippines) and those accounting for less than 0.10% (Georgia, Indonesia, Israel, Panama, Thailand and the United States), as reported in Panel C of Table 1. This step ensures that our findings are not disproportionately driven by countries with a dominant or marginal presence in the dataset, which may distort overall funding dynamics.

Additionally, we excluded observations from high-income countries, which represent only 0.03% of the sample. MFIs operating in these economies are likely to differ substantially in lending practices, funding models and risk profiles when compared to those in lower-income settings.[11]

We also applied a similar approach to address over- and under-representation at the institutional level. MFIs accounting for more than 10% or less than 0.01% of the total number of campaigns were excluded from the sample. The results, presented in Supporting Information: Table A5, remain consistent with those from our main estimations in Table 5, further confirming the robustness of our conclusions.

6 | Discussion

6.1 | Implications for Entrepreneurs

6.1.1 | Gender Funding Bias and the Role of Vulnerability-Framed MFIs

Our findings strongly indicate that gender funding biases are driven by the vulnerability orientation of MFIs. MFIs that do not follow a vulnerability-focused strategy tend to grant smaller loans to female borrowers compared to those that do. This behaviour suggests that non-vulnerability-focused MFIs prefer to pre-fund small loans, as empirical evidence shows that lenders are more likely to finance small loans quickly, especially those targeting basic needs (e.g., Gafni, Marom, et al. 2021). Conversely, vulnerability-focused MFIs strongly support female ventures by pre-funding higher business loan amounts. Increasing pre-funded business loan amounts for female entrepreneurs could help reduce their social vulnerability, as women tend to invest more in sustainable goods, use money more carefully due to their risk aversion (D'Espallier et al. 2011), and share income benefits with their households, especially their children (e.g., Eddleston et al. 2016). Thereby, business loans play a vital

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role in empowering women in low-income countries, where traditional hierarchical structures have often placed women at a disadvantage under longstanding male dominance (e.g., Cruz Rambaud et al. 2022).

The behaviour of vulnerability-focused MFIs varies significantly depending on the type of MFI, that is, those listed only on Kiva versus those also listed on Mix Market. Both types of MFIs positively moderate the pre-funding amount granted to women. However, only MFIs listed exclusively on Kiva fully bridge the gender funding gap, suggesting mission drift behaviour from MFIs listed also on Mix Market. MFIs also listed on the Mix Market can access other cost-efficient debt capital sources, thus relying less on Kiva loans. Flannery (2009) noted that posting profiles on Kiva can be time-consuming, and as competition increases, MFIs may need to spend more time and resources on polishing profiles to attract lenders. Conversely, MFIs listed only on Kiva remain more dependent on subsidies from Kiva and must strictly comply with all requirements imposed by Kiva. For instance, Kiva allows MFIs to charge interest rates but imposes limits, requiring that such rates be justifiable in terms of the sustainability of MFI efficiency (Kiva 2022). This evidence aligns with Cull et al. (2011), who showed that outreach to vulnerable people is negatively related to MFI efficiency, even for those framed as vulnerability-focused MFIs, namely MFIs also listed on Mix Market. Our findings, therefore, strongly align with framing theory, as MFIs that strongly frame their social mission and are exclusively partners with Kiva, prioritise vulnerable borrowers who align with their organisational identity—fighting poverty.

6.1.2 | Rural Funding Bias and the Role of Vulnerability-Framed MFIs

Findings related to rural borrowers are also influenced by both the vulnerability orientation of MFIs and their organisational type. Our baseline results suggest that when MFIs do not adopt a vulnerability-focused approach, rural borrowers are at a funding disadvantage. One plausible explanation of such behaviour relates to the more risk-averse orientation of commercially orientated MFIs (e.g., Cull et al. 2007), which seem to avoid the potentially negative consequences of large loans, such as over-indebtedness. This disadvantage is mitigated when MFIs align their identity with a vulnerability orientation. Despite a modest to moderate positive impact on the amount of prefunding across both types of MFIs, neither fully eliminates the funding bias—highlighting the persistent financial exclusion in rural microfinance (Mersland and Strøm 2010). According to Convergences (2019), the worldwide proportions of female (80% in 2018) and rural (65% in 2018) microfinance borrowers have problematically remained stable over the past decade.

Previous evidence aligns with these results. For instance, Kiva consistently lists agriculture as its most funded sector (Kiva 2018, 2019), and similar trends are observed on the Lendwithcare platform, where rice and vegetable farming dominate (CARE 2019). This suggests that lenders are influenced by image recognition and tend to support visible, tangible activities during the funding phase—such as specific loan types. However, they lack access to the less visible, internal funding decisions made by MFIs. As a result, rural microentrepreneurs often face bias in accessing pre-campaign funding, an opaque and private setting. This bias indicates a tendency among MFIs to prioritise financial objectives over their original social missions. As a result, there is a potential decline in agricultural lending, with MFIs redirecting their efforts toward other sectors. Smallholder farmers are often perceived as high-risk and costly clients due to the elevated transaction costs associated with managing and supervising loans in geographically remote areas. This shift occurs despite evidence in the microfinance literature showing that programmes targeting rural borrowers achieve higher repayment rates (Hishigsuren 2007; Dorfleitner and Oswald 2016), often outperforming urban-focused programmes (Morduch 1999). These findings reveal a blind spot among MFIs that claim a vulnerability-oriented identity but fail to fully address rural financial exclusion.

6.1.3 | Group Lending Funding Bias and the Role of Vulnerability-Framed MFIs

Our results related to group lending also highlight a persistent funding bias among MFIs that do not prioritise vulnerability in their organisational mission. This bias, however, is mitigated in MFIs that explicitly frame their identity around serving vulnerable populations, a similar pattern observed with female entrepreneurs and smallholder farmers. Notably, the behaviour of MFIs exhibits opposite bias depending on the type of lending technique, favouring individual loans over group loans, according with the platform they are affiliated with. MFIs exclusively listed on Kiva offset the funding gap associated with group lending. In contrast, MFIs that are also listed on MIX Market exhibit a negative moderate effect toward group lending, exacerbating funding bias. This divergence may be attributed to the fact that lenders are more responsive to individualised narratives (Galak et al. 2011). By designing funding strategies that resonate with lenders' emotional sensibilities, MFIs can enhance their prospects for rapid refinancing through platforms such as Kiva, which provides zero-interest loans. This approach reflects a strategic prioritisation of financial efficiency over purely social objectives. The weak alignment between the behaviour of MFIs and the vulnerability image they promote suggests a shift toward commercial viability rather than a steadfast commitment to social impact. Conversely, MFIs listed solely on Kiva appear to view group lending as a strategic tool to extend credit to entrepreneurs who may not qualify for or seek individual loans, functioning as a form of cohesion. This approach allows them to harness both the financial and social benefits of group lending—such as lower default rates—without compromising institutional sustainability (Zhou and Wei 2020). Grameen Bank is an example of success in microfinance.

6.2 | Institutional Priorities and Strategic Challenges

Our findings indicate that MFIs employing a prognostic framing strategy that emphasises vulnerability—specifically by targeting female and rural microentrepreneurs and group

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lending—are significantly more effective in mitigating funding bias compared to MFIs that do not adopt such an approach. Such MFIs realise that better social performance framing is more likely to inspire and motivate potential altruistic lenders to fund crowdfunding campaigns on Kiva (e.g., Figueroa-Armijos and Berns 2022). Yet lenders who offer prosocial support to vulnerable entrepreneurs still expect loan repayment (e.g., Moleskis et al. 2019). It seems that Kiva values both social return and high repayment, which are more likely from MFIs with better financial returns. Effectively, Kiva's mission 'Lend, get repaid, repeat' is used to encourage continuous support for the most vulnerable around the world (Kiva 2021b). This behaviour, even if unintended, may create an environment that promotes mission drift. Our findings carry significant implications for both MFI and governmental bodies seeking to advance equity in prosocial crowdfunding.

MFIs should move beyond symbolic signalling and embed vulnerability framing into their operational routines. This entails several strategic actions, especially among MFIs also listed on Mix Market. First, product design must be recalibrated to eliminate reliance on gender-based heuristics. MFIs should implement tiered loan structures supported by documented business plans, ensuring that loans to female entrepreneurs emphasise income generation, asset accumulation and household welfare, including education and health outcomes. A similar approach should be extended to rural borrowers by requiring detailed operational plans that specify inputs, expected yields and market access, thereby strengthening viability and reducing perceived risk. Second, MFIs should adopt operational de-risking measures, such as leveraging digital infrastructure for remote monitoring and participating in risk-sharing schemes to offset the higher transaction costs and volatility associated with rural portfolios. Additionally, MFIs must reposition group lending as a mechanism for empowerment by reinforcing joint-liability structures and articulating peer-monitoring benefits in campaign narratives to counter the identifiable victim effect and enhance lender confidence.

Governments also play a pivotal role in enabling these strategies. Policy interventions should include partial credit guarantees for agricultural portfolios to reduce systemic barriers and incentivise MFIs to expand rural outreach. Investments in digital infrastructure are essential to support connectivity and fintech solutions that lower operational costs for MFIs operating in remote areas. Furthermore, regulatory frameworks should formalise joint-liability and commitment-based structures, allowing flexible repayment schedules tailored to seasonal income cycles. Finally, harmonising badge criteria and reporting requirements across platforms will enhance transparency and prevent reputational signalling without substantive outreach.

Collectively, these interventions aim to institutionalise the positive net effect of vulnerability framing, ensuring that MFIs and governments jointly advance inclusive finance objectives while safeguarding against mission drift. By embedding these practices into governance and product design, institutions operationalise the principles of framing theory and hybrid organisational logics, transforming identity signals into actionable mechanisms that reconcile social and financial imperatives.

To qualify for a partnership with Kiva, MFIs must meet a set of criteria, including minimum thresholds for asset value and operational volume. Consequently, MFIs are required to demonstrate an established track record. Our results reveal lower funding support to vulnerable borrowers by these MFIs. As MFIs grow, their search for financial stability and commercial investments increases, and they become more supervised by regulatory entities. Consequently, they tend to respond to supervision by maintaining profit rates while reducing outreach to poor customers (Cull et al. 2011). Therefore, subsidies are necessary for institutions with strong social missions (Morduch 1999). An example is the Grameen Bank, which needed subsidies to keep its lending rates low. To offset potential mission drift effects, platform designers should move beyond uniform badge systems, as static signals risk incentivising institutional stability rather than authentic outreach. Instead, badges must be reconceptualised as performance-based credentials linked to verifiable social impact. For instance, renewal of the vulnerability badge should depend on internal audits comparing badge claims with actual allocation patterns, ensuring consistency between stated commitments and operational behaviour. Furthermore, platforms should implement systematic monitoring through monthly bias indices—tracking gender, rural and group loan allocations—to provide transparent evidence of equity performance. By embedding these mechanisms into platform governance, designers can enhance lender confidence and enable investors to align capital with genuine prosocial objectives, transforming symbolic recognition into actionable accountability.

A strategy to avoid mission drift may involve gaining profitability through improved efficiency. Scholars have distinguished between shallow sustainability (focused on the efficient use of resources) (e.g., Gutiérrez-Nieto et al. 2007) and deep sustainability (involving reevaluation of goals and system redesign) (e.g., Hill 1998), implying organisational changes. Many MFIs face significant cost and capability constraints, particularly in rural contexts, which limits their ability to implement inclusive practices effectively. Digital technologies offer a pathway to extend the impact of vulnerability framing beyond symbolic signalling and embed it into operational routines. For instance, AI-assisted narrative editors can identify missing prosocial elements—such as details on income utilisation and household outcomes—and propose plain-language revisions, thereby standardising high-quality borrower profiles across branches. Similarly, bias monitoring dashboards at the institutional level—tracking indicators such as the Gender Prefund Gap, Rural Prefund Gap and Group Prefund Net Effect—would enable monthly governance reviews that detect mission drift early. Furthermore, data-driven underwriting models, incorporating seasonality patterns and geospatial climate risk, can optimise loan sizing for rural borrowers, complementing narrative framing with calibrated risk assessment tools. Collectively, these interventions align organisational identity, product design and operational processes, transforming vulnerability framing from a one-off reputational signal into a repeatable, systematised practice.

7 | Conclusions, Contributions and Limitations

Drawing on framing theory, this study explores how MFIs strategically construct their organisational image by emphasising

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vulnerability—particularly through the use of Kiva's 'social performance badge'—to influence pre-campaign funding decisions. By explicitly focusing on pre-campaign allocation behaviour, our study provides evidence from a phase that remains largely underexplored in the crowdfunding literature.

Analysing a sample of 140 MFIs across 59 countries, we distinguish between MFIs exclusively listed on Kiva and those also featured on Mix Market, examining how they allocate funding to three categories of vulnerable borrowers. Given the unique dynamics of crowdfunding, especially the distinction between campaigns for basic needs versus entrepreneurial activities, our focus on business loans is essential. These loans, being income-generating, hold greater potential to empower marginalised and vulnerable communities.

Using multilevel modelling, we identify significant funding biases among MFIs not awarded Kiva's vulnerability badge. This bias is observed across all three borrower groups—female, rural and group borrowers. However, when MFIs adopt a vulnerability-framed orientation, the funding pattern shifts. While both types of MFIs show a positive moderating effect on loan amounts, only those exclusively listed on Kiva fully overcome the funding gap for women and group borrowers and partially attenuate the gap for rural borrowers. By contrast, MFIs listed on both Kiva and Mix Market display weaker positive moderation for female and rural borrowers and exacerbate the bias against group loans. This divergence reflects differing institutional priorities: MFIs reliant on Kiva's zero-interest capital appear more mission-aligned, whereas those with access to alternative funding channels (e.g., Mix Market) may adopt more commercially driven strategies.

This bias, particularly regarding group loans, may also reflect the emotional appeal of individual narratives, which are known to resonate more strongly with socially motivated lenders (Galak et al. 2011). Thus, MFIs may design funding strategies aligned with storytelling preferences to optimise refinancing opportunities on platforms like Kiva. In this context, the practice of awarding vulnerability badges to more financially stable MFIs (e.g., those also listed on Mix Market) may reflect an institutional preference for low-risk partners under the guise of social performance recognition.

This study advances framing theory in the context of prosocial crowdfunding by shifting the analytical lens from campaign-level entrepreneur narratives and lender perceptions to organisational identity framing at the institutional level. We demonstrate that MFIs strategically construct a vulnerability-oriented identity—signalled through platform badges—to influence resource allocation in the pre-campaign phase, a private and underexplored stage of the crowdfunding process. In doing so, we broaden the scope of framing theory beyond individual actors to encompass hybrid organisations that operate under dual logics of social mission and financial sustainability. Drawing on framing perspectives, we further show how MFIs' self-categorisation as 'pro-poor' or 'vulnerability-focused' systematically shapes lending behaviour. By integrating identity framing with allocation decisions, the study offers a clear mechanism explaining why some MFIs prioritise vulnerable borrowers despite commercial pressures, while others exhibit mission drift. This enriches hybrid organisation scholarship by connecting identity signalling to strategic funding choices and clarifying how institutional identity mediates trade-offs between social and commercial objectives. We also conceptualise vulnerability bias as the systematic differences in prefunded loan amounts allocated to borrower groups (female, rural and group lending) during the pre-campaign stage. This concept extends bias discussions in crowdfunding—typically centred on lender stereotypes—to the institutional level, highlighting MFIs as active agents in shaping equity outcomes. By operationalising vulnerability bias and testing its interaction with framing strategies, the study provides a foundation for future research on institutional determinants of inclusion in digital finance ecosystems. Finally, we situate framing theory within a multi-level design (loan-level and MFI-level), showing how organisational framing interacts with borrower characteristics to affect funding outcomes. This approach responds to calls for integrated theoretical frameworks that capture the interplay between micro-level narratives and macro-level institutional strategies in crowdfunding environments. Empirically, the study addresses recent calls for deeper insight into funding-related decision-making across the stages of crowdfunding by documenting MFI behaviour in the pre-campaign phase and offering the first large-scale quantitative analysis of institutional framing before public exposure. The evidence illuminates institutional heterogeneity behind platforms and shows how it shapes equity and inclusion: while vulnerability framing can mitigate or even reverse disadvantages for certain borrower groups, MFIs' access to alternative funding channels and governance pressures produce divergent allocation patterns. Moreover, by examining MFI behaviour in private, non-transparent phases, the study reveals that even MFIs holding vulnerability badges may display signs of mission drift, suggesting that recognition mechanisms can inadvertently privilege financial over social priorities under specific institutional conditions. Together, these empirical insights complement our theoretical contributions, offering a comprehensive account of how organisational identity framing operates within hybrid microfinance organisations and materially influences equity outcomes in prosocial crowdfunding.

This study is not without limitations. First, we lack detailed insight into pre-campaign processes, including borrower selection criteria, alignment between requested and approved amounts, and how MFIs monitor loan duplication across platforms. Second, we do not analyse post-funding outcomes, limiting our ability to evaluate long-term borrower empowerment. While microcredit is often positioned as a poverty alleviation tool, its effectiveness is disputed, with some critics arguing that it reinforces existing inequalities (Rankin 2002). Third, the transparency of Kiva's partner selection process is limited. Although extensive documentation is requested (e.g., financials, projections), the specific thresholds and criteria remain undisclosed, making it difficult to assess the alignment between Kiva's mission and MFI practices.[12]

Despite certain limitations, our findings offer valuable insights for policymakers, platform designers, governments and MFIs. As MFIs continue to navigate the tension between financial sustainability and social impact, leadership within these institutions should prioritise the adoption of technological innovations—particularly digitalisation. However, we acknowledge

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that many MFIs face significant barriers to technological adoption, including high costs and infrastructural limitations, especially in underserved regions. In this context, governments have a critical role to play by investing in foundational infrastructure that supports digital financial services. Regulatory and governance challenges also remain central. Issues such as limited transparency and weak internal controls can erode institutional credibility. Harmonising regulatory frameworks across countries could contribute to a more stable and trustworthy microfinance sector. Furthermore, client education and financial literacy continue to pose challenges for both MFIs and their clients. A lack of understanding of basic financial concepts often excludes vulnerable populations from accessing microfinance services or leads to the misuse of funds and unrealistic expectations regarding loan terms and repayment, thereby increasing the risk of over-indebtedness. In the context of prosocial crowdfunding, MFIs have considerable scope to refine their framing strategies to attract greater attention from socially motivated lenders. Additionally, emerging global challenges—such as climate change—pose significant risks to both MFIs and their clients. Vulnerable borrowers are increasingly exposed to economic shocks, natural disasters and political instability, all of which can disrupt MFI operations and impair clients' repayment capacity.

Acknowledgements

The authors would like to thank the Editor, the editorial assistant, and the reviewers for their insightful comments and suggestions, which have greatly contributed to improving the quality of this manuscript.

Funding

This research was financed by Portuguese public funds through FCT—Fundação para a Ciência e a Tecnologia, I.P., under the projects PTDC/EGEOGE/31246/2017, UID/4105/2025, UID/315/2025, and UIDB/05037/2025 (DOI: 10.54499/UIDB/05037/2025).

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available in Kiva Data Snapshots at https://www.kiva.org/build/data-snapshots. These data were derived from the following resources available in the public domain: Downloading Snapshots CSV, http://s3.kiva.org/snapshots/kiva_ds_csv.zip; Downloading Snapshots JSON, http://s3.kiva.org/snapshots/kiva_ds_json.zip.

Endnotes

[1] By *funding bias* we refer to systematic differences in the loan amounts pre-funded by MFIs across borrower groups. In this context, a funding bias occurs when MFIs consistently allocate higher or lower pre-funding amounts to specific categories of borrowers (e.g., women, rural borrowers or group borrowers) relative to others. This definition closely aligns with the concept of bias discussed in prior crowdfunding research, particularly studies on investor stereotypes and differential treatment in funding decisions (e.g., Johnson et al. 2018).

[2] The literature refers to this type of funding as a business-purpose loan or a loan for productive purposes (e.g., Johnston Jr and Morduch 2008).

[3] Allison et al. (2013) provides a comprehensive description of the pass-through model of financing. The funding timeline in Figure 1 matches the major steps of this pass-through model as follows: (1) the precampaign phase corresponds to Allison et al.'s Step 1 (entrepreneurs apply for a loan) through Step 4 (MFIs write loan profiles with entrepreneurs' cooperation), (2) the funding phase matches step 5 (posting loan profile) and Step 6 (evaluation of loan profile, loan is fully funded or not), and (3) the post campaign phase corresponds to Step 7 (reimbursement of lenders) until the end of the process.

[4] Kiva recognises lending partners through seven Social Performance Badges: Vulnerable Group Focus (hereafter 'Vulnerability'), Anti-Poverty Focus, Client Voice, Family and Community Empowerment, Entrepreneurial Support, Facilitation of Savings, and Innovation, each highlighting organisations demonstrating exceptional commitment to specific aspects of social impact (Kiva 2025).

[5] A notable exception is Figueroa-Armijos and Berns (2022).

[6] The redesign sought to enhance the user experience and help monitor loans within each crowdfunding campaign profile. Thus, lenders can readily assess the performance of any MFI (Anglin et al. 2020).

[7] This adjustment corrects for differences in purchasing power, cost of living, and currency valuation across countries, allowing for meaningful and comparable assessment of loan sizes. It also mitigates potential biases linked to varying levels of economic development, enabling a more accurate cross-country comparison of microloan funding dynamics.

[8] Interest-rate information is not consistently disclosed across MFIs on Kiva and therefore cannot be reliably used in our analysis. Since MFIs refinance through Kiva at a zero-interest rate, the pre-funding decisions examined in this study are primarily driven by organisational strategies and framing choices rather than loan pricing policies.

[9] Full descriptive statistics by MFI type are available on request.

[10] To estimate CRE and MLRE models we use the mixed command of Stata 17.

[11] For example, Kiva only adopts a P2P model for direct loans in the United States (Dorfleitner et al. 2021).

[12] We also acknowledge the possibility that MFIs differ in the extent to which they benefit from subsidies or reputational incentives in repeated crowdfunding interactions. We thank the anonymous reviewer for bringing this to our attention. While these mechanisms are theoretically relevant, detailed information on subsidy levels is not consistently available in Kiva's public dataset nor systematically disclosed through MIX Market for our study period. Consequently, these aspects could not be empirically examined in the present study but represent a promising avenue for future research.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table A1** Loans granted by MFI. Column 'Listed': 0 if MFI listed only on Kiva; 1 listed on Kiva and on Mix market. **Table A1. (*Cont*)** Loans granted by MFI. Column 'Listed': 0 if MFI listed only on Kiva; 1 listed on Kiva and on Mix market. **Table A1. (*Cont*)** Loans granted by MFI. **Table A2**. Multilevel Diagnostic Test Full Sample. Dependent variable: ln(Normalized APreF +1). **Table A3**. Robustness Checks—Endogeneity Diagnosis (Two-Stage Residual Inclusion—2SRI). **Table A4**. Robustness Checks—Sample distribution. MLRE, Random Intercept. Dependent variable: ln(Normalized APreF +1). **Table A5**. Robustness Checks by Country and MFIs. MLRE, Random Intercept. Dependent variable: ln(Normalized APreF +1).

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