Expand or Avoid: Microfinance Credit Risk and Climate Vulnerability

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Abstract

This study investigates the association between climate vulnerability, geographic expansion and credit risk in microfinance institution's (MFIs) loan portfolios. It is motivated by inconclusive evidence concerning the climate vulnerability-bank risk nexus and the geographic expansion-bank risk nexus. Applying system generalized method of moments (GMM) to a sample of global MFIs over the period 1999-2019, we report evidence that climate vulnerability and geographic expansion increase MFI credit risk. The risk is more pronounced for non-shareholder-owned MFIs compared to shareholder-owned MFIs. This suggests MFI expansion into climate prone regions is curtailed in the case of shareholder-owned MFIs to minimize credit risk, overshadowing the microfinance mission to provide banking services to the poorest and the most vulnerable. In addition, we report evidence that climate vulnerability moderates the consequences of geographic diversification in the microfinance industry.

1. Introduction

Microfinance Institutions (MFIs) provide alternative access to finance for the poor and have been growing rapidly with current loans of $124 billion and 140 million customers globally (Sun & Liang, 2021). The microfinance industry experienced record growth between 2004-2008, when the annual growth rates for the number of borrowers and loan portfolios averaged 21 percent and 34 percent, respectively (Yimga, 2018). Microfinance's potential to facilitate poverty alleviation and their mission to bridge the financial inclusion gap could lead MFIs to become the largest banking market in the world, in terms of clientele number (Beisland et al., 2019). MFIs that are motivated by institutional logic may seek economies of scale through geographical expansion. However, MFI expansion into different regions also triggers concern about loan delinquency, defaults or over-indebtedness (e.g., resulting from a lack of knowledge about the market). These concerns are magnified when MFIs expand into climate vulnerable regions. Since most of MFIs loans are linked to agriculture and smallholder farming, climate vulnerability is assumed to be a key risk driver for rural micro-lending (Giné & Yang, 2009; Möllmann et al., 2020).

This paper explores how climate vulnerability and geographic expansion affect the credit risk of microfinance loan portfolios both separately, and by investigating the combined effect of the interaction between the two. Among the many pressing issues facing MFIs, credit risk ranks the highest (Zamore et al., 2019). Two key factors that make MFI's loan portfolios exposed to credit risk are semi- or un-collateralised loans and short repayment time (Mersland & Strøm, 2009). MFIs have grown and expanded their geographical reach, this is particularly true in rural areas (Chikalipah, 2019). MFI expansion is aligned with microfinance social goals; however, the performance benefits of MFI growth are unclear. While greater MFI diversification can reduce geographic risk, it may lead to agency problems. In addition, physical risks associated with climate change are increasingly recognised as financial risks (TCFD, 2018). MFIs serve clients in countries that are particularly exposed to flooding, heat stress and other climate change associated hazards. Further, MFI clients in these countries are ill-prepared to deal with climate-related natural disasters due to their low incomes (Hallegatte & Rozenberg, 2017; Hertel & Rosch, 2010). As a consequence, MFI clients are highly vulnerable[1] to these anthropogenic hazards[2] that have been increasing in magnitude and frequency (IPCC, 2018) and thereby are likely leading to greater credit risk exposure for MFIs. Whether MFI geographical diversification increases or reduces credit risk in the context of climate change is not clear. On the one hand, diversification may reduce exposure by spreading credit risk over a wider geographical area. However, on the other hand, diversification might increase exposure as MFIs expand to areas with greater climate vulnerability. Given the threat posed by anthropogenic climate change, understanding the interaction between climate vulnerability and geographic expansion in the context of MFIs is important and timely.

Modern portfolio theory suggests that banks can achieve large reductions in risk through portfolio diversification. In particular, a bank's geographic expansion can lead to earnings diversification, which then reduces bank risk, and enhances efficiency through economies of scale (Bandelj, 2016; Goetz et al., 2016). Diversified banks may also enjoy better stability due to their cost-efficient operations (Diamond, 1984; Boyd & Prescott, 1986). For example, banks that expand across regions can generate better profitability, while reducing earnings volatility, market risk, and insolvency risk (Deng & Elyasiani, 2008; Chu et al., 2020).

[1] We employ the definitions for vulnerability, hazard and risk used by the United Nations Office for Disaster Risk Reduction (UNDRR). Vulnerability refers to the "conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards" (UNDRR, see: https://www.undrr.org/terminology).

[2] Hazard refers to "a process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation" (UNDRR, *op. cit.*). However, in this study, by hazard we refer to anthropogenic hazards, or human-induced hazards, which are induced entirely or predominantly by human activities and choices. This term does not include the occurrence or risk of armed conflicts and other situations of social instability or tension which are subject to international humanitarian law and national legislation.

By contrast, agency theory suggests that bank's geographic expansion ignites agency problems. It is evident from agency-based corporate expansion models that bank managers may prefer expansion, however the larger territory may lead to compromised loan quality (Berger & Ofek, 1995; Denis et al., 1997; Jensen, 1986; Servaes, 1996). Expansion and distance raise the complexity for bank headquarters to monitor their branches (Berger et al., 2005), affecting their ability to manage risk and monitor lending (Acharya et al., 2006; Winton, 1999; Zamore et al., 2019). Bankers may prioritise their personal goals over bank goals in environments with weak governance and poor monitoring (Bandelj, 2016). As a result, banks face high agency costs. Reflecting on the competing theoretical explanations, empirical research exploring whether geographical diversification improves or deteriorates credit risk has yielded mixed findings (Bandelj, 2016).

The linkage between climate vulnerability and microfinance is an emerging issue in the literature (Dowla, 2018; Johnson et al., 2019). However, most of the studies consider the role of MFIs in supporting the borrower's ability to adapt and develop resilience to climate change (Agrawala & Carraro, 2010; Fenton et al., 2017; Dowla, 2018). To date, the effect of climate change on MFI bank-level risks, such as aggregate credit risk in their loan portfolios, has received little attention in the literature. Fenton et al., (2017b) and Klomp (2018) are notable exceptions (discussed further below). In related research, Möllmann et al. (2020) and Pelka et al. (2015) examine farmer's vulnerability to adverse weather events and credit risk for agricultural MFIs. The authors report a positive correlation between adverse weather events and credit risk based on a single MFI in Madagascar. This finding suggests that MFI credit risk increases with the expansion of loan portfolios into climate vulnerable regions. Hence, more conservative MFIs may limit their positioning and lower their presence in zones designated to have high weather risk. Similar claims were made by Johnson et al. (2019) and Khan & Rabbani (2015) who reported evidence of MFIs' reduced presence in climate hazard prone areas.

Zamore et al. (2019) found that despite the importance of the geographic expansion-bank risk nexus, limited attention has been paid to this issue in the microfinance literature. The authors find initial evidence that geographic expansion is associated with greater MFI credit risk (Zamore et al., 2019). However, the extant literature has not examined the effect of geographic positioning to MFI risk in the context of climate vulnerability. On the other hand, Klomp (2018) also reports an initial finding that financial risk in MFIs increases if any natural disaster happens. However, the author's attempt did not include a measure of MFI geographic expansion and focussed on natural disasters alone. This study analyses the impact of climate vulnerability and geographic expansion on MFI credit risk and identifies how these effects interact with credit risk. Our unbalanced panel sample covers the period 1999-2019, spanning 21 years and includes 119 countries and 2,591 MFIs.

Investigating the effect of geographic expansion and climate vulnerability on credit risk yields endogeneity concerns. First, MFI geographic expansion is 'mission' driven by the desire to provide banking services in remote areas. However, this decision is often endogenous as MFIs see it also as a strategic choice to be undertaken when the benefits are deemed to outweigh the expenses and risks (Zamore et al., 2019; Chu et al., 2020). Second, there is a notable variation in climate vulnerability data since some countries are severely affected, while others are not and this may add some endogeneity issues (Klomp, 2018). Third, there is a potential omitted variable bias issue—given that credit risk and expansion could be explained by other factors (Campa & Kedia, 2002; Chu et al., 2020). As a result, static regression models may report spurious results. To solve these empirical challenges, we exploit the two-step system GMM developed by Arellano and Bover (1995) and Blundell and Bond (1998). We also show our findings are robust to different climate and credit risk measures.

To the best of our knowledge, this is the first systematic study to address the effects of climate vulnerability and geographic expansion on the credit risk of microfinance loan portfolios using a large-scale global dataset. We document that MFI geographic expansion positively affects credit risk, complementing Zamore et al., (2019), who also find similar evidence of positive correlation between geographic expansion and credit risk. Our findings stand on the propositions of agency theory – this is perhaps unsurprising given mission may outweigh profit motives for a large proportion of MFIs. Additionally, we also report that climate vulnerability increases MFI credit risk, complementing Klomp (2018) who reported that natural disasters have increased MFI's risks including deteriorating credit quality. Our findings also complement Möllmann et al. (2020) who report that one agricultural MFI in Madagascar experienced overdue instalment payment risk following adverse weather events. Collectively, Klomp (2018), Zamore et al., (2019), Möllmann et al. (2020) and our study suggest that MFIs face high credit risk due to their climate vulnerability and expansion into different markets, likely reflecting expansion in remote, climate prone regions.

Further, using our large international sample, we explore the country specific and case study findings of Khan and Rabbani (2015) and Johnson et al. (2019) that regions prone to adverse weather shocks have lower MFI footprints. Given that anthropogenic climate change hazards, as exogenous shocks, will likely have the highest impacts on MFI credit risk in regions and countries with high climate vulnerability, we interact climate vulnerability as a moderator in the relationship between geographic expansion and credit risk. We test the interaction role of climate vulnerability and find a negative coefficient. The result suggests that MFIs reduce expansion into climate vulnerable areas as a way of mitigating credit risk. We also show that these findings vary depending on the MFI ownership structure. For example, banks, rural banks and non-bank financial institutions (NBFIs) which are shareholder-owned, experience lower credit risk. Conversely, credit risk is more pronounced among non-shareholder-owned MFIs such as non-governmental organizations (NGOs), credit unions and cooperatives. This suggests MFI expansion into climate prone regions is curtailed in the case of shareholder-owned MFIs to minimize credit risk, overshadowing MFI's mission to provide banking services to the poorest and the most vulnerable. Our findings about ownership components complement the work by Zamore et al. (2019). The significance of the relationship for non-shareholder ownership structure brings into question the role of shareholder-owned MFIs in the context of climate change where those most vulnerable to climate change will need financing for mitigation and adaptation efforts.

The rest of the paper is organized as follows. Section 2 develops research hypotheses, Section 3 deals with data and measurement, Section 4 outlines the methodology including empirical models. Section 5 presents the empirical results and robustness checks and Section 6 provides concluding remarks.

2. Hypotheses

Like banks, MFIs are subject to various risks such as credit, country currency, interest rate risk, liquidity, market, and operational risk. MFIs' novel intention to provide financial access to the poorest is also associated with risk. Information asymmetry between lenders and borrowers, unreliability of borrowers' financial data, absence of conventional collateral are some examples of the sources of uncertainty that make microfinance lending riskier than traditional lending by conventional financial institutions. Credit risk is typically the key risk driver for MFIs as the provision of microcredit is their main activity (Armendáriz & Morduch, 2010). Credit risk is the risk that a borrower defaults on their contractual financial obligations.[3] As noted in Assaf et al. (2019), the global financial crisis clearly demonstrated the consequences of credit risk for bank survival and prosperity. Higher loan ratios in banks often lead to greater credit risk (Assaf et al., 2019). MFIs are not resistant to the effects of credit risk

[3] The Basel Committee (BIS, 2000) defines credit risk as "the risk that a borrower will default on any type of debt by failing to make required payments".

given their concentrated focus on lending. MFI clients are also subject to shorter repayment frequencies which can compound repayment pressure leading to loan default on interest and principle obligations. According to Möllmann et al. (2020) the common contract of provision for microcredit is small in size and requires frequent instalments within short periods that start immediately after borrowing. Loan delinquencies over the whole period harm the viability of MFIs. Arun (2005) explains that once a loan is in arrears (even for as little as two weeks) it is difficult to recover and it may affect the sustainability and viability of the microfinance industry.

As noted in the *Introduction*, MFI's serve clients in countries that are particularly vulnerable to climate-related natural disasters due to their geographic location and low incomes (Hallegatte & Rozenberg, 2017; Hertel & Rosch, 2010; IPCC 2018). The highly vulnerable MFI clients to increasing anthropogenic hazards are likely leading to greater credit risk exposure for MFIs. Accordingly, we propose the following hypothesis to test the climate vulnerability-credit risk nexus:

H1a. *Climate vulnerability is associated with an increase in microfinance credit risk.*

An noted in the *Introduction*, expansions in a new region may come with limited market information and experience which can affect value loss and intensify agency problems (Deng & Elyasiani, 2008). MFIs and banks alike may have less information about new geographic regions. This subjects them to greater uncertainty and risk of value loss when loans are granted without full knowledge of the risk involved. The risk exposure is compounded by the fact that managers may choose to act in their own self-interest (Goetz et al., 2016). Examples of MFI agency costs include perquisite consumption or possibly lending to more risky clients because of personal interest or agreeing to more risky loans because of additional incentives that are offered through the loan arrangements (e.g. gifts or other payoffs to secure the loan).

By way of contrast, geographic expansion involves acquiring diverse assets and potentially reducing idiosyncratic risk (Goetz et al., 2016; Chu et al., 2020). Financial institutions can use geographic expansion to diversify their loan portfolios (Markowitz, 1968) to benefit from the imperfect return correlations between different asset classes over time. According to portfolio theory, banks can expand across several geographic locations to minimize their loan portfolio credit risk (Liang & Rhoades, 1988; Emmons et al., 2004). A bank's geographic expansion can also lower net income variability and raise the efficient risk-return frontier (Liang and Rhoades, 1988). In the context of MFIs, loan portfolio geographical diversification may reduce credit risk because MFI loans are distributed among several borrowers in different regions. Additionally, geographic expansion is also beneficial for deposit-taking MFIs to minimize liquidity risk by diversifying the deposit portfolio and reducing the variance of deposit flows (Liang & Rhoades, 1988).

Overall, it is not clear if MFI geographic expansion will have positive or negative effect on the credit risk of MFI loan portfolios – agency theory and portfolio theory provide contrasting *ex ante* expectations. Thus, the following hypotheses are proposed to examine the geographic expansion-credit risk nexus:

H2a. *Geographic expansion is associated with an increase in microfinance credit risk.*

H2b. *Geographic expansion is associated with a decrease in microfinance credit risk.*

Referring to the claims of Khan and Rabbani (2015) and Johnson et al. (2019) that MFIs are less accessible in climate prone areas, we propose the following Hypothesis to examine the interaction of climate vulnerability and geographic expansion.

H3. *Climate vulnerability moderates the consequences of geographic expansion on microfinance credit risk.*

3. Data and variables

3.1. Sampling and data

The study uses an unbalanced panel sample of 2,591 MFIs from 119 countries with time span of 21 year (1999-2019).[4] The dataset is compiled from various sources, each with some strengths and weaknesses. Individual MFI data were collected from the Microfinance Information Exchange on MIX market platform[5], a not-for-profit private organization that intends to facilitate exchanging information in the microfinance sector. MIX is the most reliable and explicit, publicly accessible data source for MFIs providing wide scale coverage (Cull et al., 2009; Klomp, 2018). According to Mersland and Strøm (2009) the biggest shortcoming of MIX market is the voluntary self-reporting nature. The authors argue this may cause a reporting bias due to the absence of third-party verification. Despite these concerns, MIX market is the most widely used database in microfinance research (Ahmad et al., 2020; Klomp, 2018; Servin et al., 2012; Tadele et al., 2018a, 2018b; Wijesiri, 2016). We further take Kaufmann et al. (2010) Governance Index to control country-level institutional quality. Finally, we extract macroeconomic data from the World Bank's World Development Indicators (WDI) database.[6]

3.2. Measuring geographic expansion

In today's era of digitalization in the financial system, branching is still critically important for banking operations, particularly to scale up their share of deposits (Aguirregabiria et al., 2016). Due to extensive competition in the markets, banks may choose to diversify geographically to increase their chance of scaling up. This diversification takes place when banks expand their physical presence across the region or extend their branch network in different locations. Therefore, both the number of branches and the number of geographic

[4] Refer to Appendix A for the sample distribution by country.
[5] MIX is currently hosted by the World Bank data catalogue; https://databank.worldbank.org/source/mix-market.
[6] The macroeconomic data were sourced from the World Bank's World Development Indicators database; https://databank.worldbank.org/source/world-development-indicators.

markets (interstate operations) are both common proxies to measure bank geographic expansion in the literature (Fraser et al., 1997; Goetz et al., 2016).

However, there is debate about the number of branches as an appropriate measure of geographic expansion. According to Deng and Elyasiani (2008), the branch measure does not calculate the exact distance between a bank's headquarters and a branch location. In contrast, Zamore et al. (2019) use the number of branches rather than the physical distance. Similar to the agency theory proposition, Zamore et al. (2019) argue that bank complexity increases as the number of branches increases and branch-level monitoring becomes more difficult. Hence, we use the number of branches as a proxy measure for geographic expansion, consistent with Hughes et al. (1996), Aguirregabiria et al. (2016) and Zamore et al. (2019).

3.3. Measuring climate vulnerability

We use the Notre Dame Global Adaptation Index (ND-GAIN)[7] as our primary climate vulnerability data source. The ND-GAIN index measures a country's current vulnerability to climate disruptions and assesses a country's readiness to leverage private and public sector funds for adaptation (Chen et al., 2015). The index brings together 74 variables to form 45 core indicators for 181 countries to measure their vulnerability to climate change and their readiness to adapt.[8] The climate vulnerability measure in the ND-GAIN framework is encapsulated from exposure, sensitivity and adaptive capacity components. Comparatively, the readiness measure in the ND-GAIN index is combined from economic, governance and social components.

A country's climate vulnerability is determined by its geographic setting, which may not be endogenous. Though some components in the climate vulnerability measure may be

[7] The index formerly housed in the Global Adaptation Institute in Washington, D.C. However, it moved to the University of Notre Dame in 2013 and since then it has been part of the Climate Change Adaptation Program of the University of Notre Dame's Environmental Change Initiative (ND-ECI). The ND-GAIN framework is based on the Intergovernmental Panel on Climate Change (IPCC) review process, published peer-reviewed materials and relevant agencies' feedback. It is currently the most comprehensive and granular database for our purpose.

[8] Chen et al. (2015) outlines the detailed data sources and methodology to construct the Notre Dame Global Adaptation Index (ND-GAIN) in a technical report. We refer to the report for variable definitions and thorough explanations. See Appendix B which outlines the underlying measures used in the construction of the ND-GAIN framework.

influenced by a country's economic, political and social settings, e.g. adaptive capacity. So, it is inherent that climate vulnerability measures may cause endogeneity concerns. However, this issue is likely to be more severe when employing readiness measures from the ND-GAIN framework. Since we also include several country-level economic indicators and institutional quality index (IQI), the readiness measures are tended to be highly correlated. Therefore, following (Kling et al., 2021), we consider ND-GAIN data as our variable of interest and the issue of endogeneity is further discussed in estimation method (see Section 4.2).

Additionally, we employ climate-related disaster damage data which are sourced from the Emergency Events Database (EM-DAT) to perform robustness tests.[9] Not all disasters reported in EM-DAT were caused by climate change. The database classifies four different groups of natural disasters: (i) geophysical disasters including earthquake, tsunami and volcanic eruptions; (ii) meteorological disasters entails extreme temperature, storms and hurricanes; (iii) hydrological disasters are concerned with floods and landslides; and (iv) climatological disasters entail droughts, glacial lake outbursts (sea level rise) and wildfires. Our focus is to capture the effects of climate-related disasters; thus, we only include disaster groups (ii), (iii) and (iv) in our sample.

We further denote three measures of climate-related disaster damage from EM-DAT's essential core data, which set to act as proxies for the magnitude of the climate-related disasters. They are (i) the total number of people killed, (ii) the total number of affected population and (iii) the total amount of direct economic damage (measured in the U.S. dollars). This paper considers both frequency and magnitude of climate-related disasters, hence, we employ the economic damage measure, which is the aggregated economic loss from all climate-related disasters in a year. Therefore, following Noy (2009) and Nguyen et al. (2020), we construct a

[9] EM-DAT is hosted by the Centre for Research on the Epidemiology of Disasters (CRED) and contains essential world-wide disaster data from as early as 1900 to present day. EM-DAT is widely cited in the climate-related literature (Noy, 2009; Klomp, 2014, 2018; Nguyen, et al. 2020).

climate-related disaster damage variable (DAMAGE) by calculating a ratio from the total economic loss to the country prior year gross domestic products (GDP). In brief, DAMAGE denotes the total economic loss caused by all climate-related disasters in a particular country, in a given year, and standardized by the country's prior year GDP.

Accuracy around the measurement of EM-DAT data, as well as empirical concerns such as endogeneity associated with the database mean that the measure of climate-disaster economic damage could be endogenous to our macroeconomic factors (Klomp, 2014; Nguyen, et al. 2020). One way to treat this type of empirical concern is to employ an instrumental variable in the model. The system GMM methodology allows for the inclusion of valid internal instrumental variables as a treatment to endogeneity issues. Given the thresholds that EM-DAT applies, the database does not reflect the complete universe of disaster events (Felbermayr & Gröschl, 2014). For example, the EM-DAT only records a disaster if it causes 10 or more deaths, 100 or more people are affected/injured/homeless, the country declares a state of emergency or appeals for international assistance. Conversely, the DesInventar database considers an event a disaster if it causes one or more human deaths or incurs costs of $1 or more in the economy (Osuteye et al., 2017).[10] This study uses ND-GAIN as our baseline climate vulnerability data source. We demonstrate the robustness of our results using the EM-DAT climate-related disaster data.

3.4. Measuring credit risk

Several proxies have been used to measure credit risk in the literature (Shahriar & Garg, 2017; Zamore et al., 2019). Our first measure is *Non-Performing Loans* (NPLs). In the banking literature NPLs are defined as the sum of total loans and leases arrears for 90 days or more (Ghosh, 2015). The short-term nature of microfinance loans (Möllmann et al., 2020), means

[10] The data sources for both of the databases is also different. Osuteye et al. (2017) report that EM-DAT compiles data from United Nation (UN), government and non-government agencies, insurance companies, research centres, news agencies. On the other hand, DesInventar database uses national and local newspapers, police and public health reports as data sources.

that NPLs are commonly referred as *portfolio at risk* for 30 days or more (PaR30). Previous studies have also used NPL to measure credit risk. For example, Shahriar and Garg (2017), Zamore et al. (2019) and Möllmann et al. (2020) all use NPLs. PaR30 is referred as the outstanding portion of a microfinance loan portfolio that is past due 30 days plus the renegotiated portfolio scaled by gross loan portfolio. A higher PaR30 ratio implies the less able borrowers can repay their loans within 30 days and majority are in arrears for longer than a month, indicating greater MFI credit risk.

The second metric that we use is *Loan Loss Provisions* (LLP). Generally, LLP is the share of reserved loan to attenuate future loan losses. This metric has been used in banking research (Vithessonthi, 2016) as well as in microfinance studies (Ahlin et al., 2011; Shahriar & Garg, 2017; Zamore et al., 2019) to measure the credit risk. The *Write-off ratio* is another proxy that measures MFI credit risk. Following Shahriar and Garg (2017) and Zamore et al. (2019), we employ the write-off ratio in this paper. The ratio is referred as the proportion of loan in the MFI's portfolio that is written off and recorded as a loss. Briefly, it indicates a MFI's economic ability to manage an anticipated future loan loss. We also attempt several robustness tests using additional credit risk proxies. Following Zamore et al. (2019), we calculated a composite risk metric by summing PaR30 and LLP. We also construct a zCCR using this composite risk metric.

3.5. MFI-level variables

Income diversification. Chaibi and Ftiti (2015) and Ahmed and Mallick (2019) use non-interest income divided by total operating income as a proxy of income diversification. These off-balance sheet activities of an MFI indicate the diverse source of revenue generation for the firm. MFIs may rely upon alternative types of income other than interest income to offset their shortfall in interest margins on financing services (Lassoued, 2017).

MFI size. Chaibi and Ftiti (2015) assert that large banks are willing to take more risks, referring to the presumption of 'too-big-to-fail'. Too-big-to-fail attitude had a severe impact on the financial system, and currently it is among the key elements of stability in the global finance. Theoretically, the physical diversification of MFIs is influenced by their size (Zamore et al., 2019), because large MFIs have capacity to operate and monitor their branches in multiple locations. Size is also critical for MFIs to offset their covariate risks, such as climate-related risk. Small MFIs are more vulnerable to natural disasters, while large MFIs are more able to manage the risks (Klomp, 2018). We use logarithm of total assets to control for MFI's size effect.

Equity capital. According to Dangl & Zechner (2004) exposure of bank's credit risk is tied to their equity requirements in many countries, since Basel Accord II proposes to regulate the link explicitly. While Zamore et al. (2019) note that the level of credit risk exposure in MFIs may be driven by the different capital structures. We use the equity to total assets ratio to control for the risk-taking behaviour of MFIs.

Ownership type. MFI's credit risk may also be determined by their legal structures or ownership types which in turn can influence the use of various monitoring and control systems. For example, microfinance NGOs typically focus on their social mission and the poor's welfare, thus they will reach out to more rural communities across regions. Agency theory suggests that there is a lack of monitoring in microfinance NGOs due to the absence of owners, which may cause excessive risk-taking by managers (Galema et al., 2012). This complexity may be compounded when microfinance NGOs are geographically diversified, leading to greater credit risk exposure. In contrast, microfinance banks are more closely monitored by shareholders, in addition to regulation through each country's central bank authority or autonomous regulatory and supervisory agency. To control for the effect of ownership, we follow Zamore et al. (2019) and categorize our sample according to two ownership types. First, shareholder-owned MFIs consist of microfinance banks, rural banks and non-bank MFIs. Second, non-shareholder-owned MFIs comprise of microfinance NGOs, credit unions, cooperatives and others. We also group the dataset in *Panel A (shareholder-owned MFI)* and *Panel B (Non-shareholder-owned MFI)* to examine vulnerability-expansion-risk nexus across ownership structures.

MFI maturity. As MFIs mature their experience and skill in risk management and dealing effectively with potential defaults increases. Mature MFIs are arguably better positioned to control credit risk, because of the business knowledge gained over time and greater operational efficiencies (Zamore et al., 2019). Time spent in business operations is positively correlated with attaining cost-efficiency (Caudill et al., 2009). Efficient MFIs should be well-positioned in term of credit risk, as well as diversifying their presence in different geographic locations. Following the MIX market definitions, we categorize business experience according to three levels.[11] These are (i) *new* (0 to 3 years in operations); (ii) *young* (4 to 7 years in operations); and (iii) *mature* (8 years and above in operations).

Lending methods. There is little or no collateral against microfinance loan portfolios, thus MFIs are subject to a greater credit risk challenge (Armendáriz & Morduch, 2010). MFI's manage this uncertainty by initiating innovative lending methods and group lending is deemed to be the hallmark of MFI's high repayment success (Mersland & Strøm, 2009). This lending method works via mutual insurance among the microfinance borrowers, that means members in a group are jointly liable for the default of another member (Zamore et al., 2019). According to De Quidt et al. (2016) group lending also provides a cost advantage to MFIs since it may reduce lending transaction costs when compared to individual loan contracts. We control for group lending since it is expected that this form of lending has a lower risk of default.

[11] Zamore et al. (2019) use the number of years in operation as a proxy for experience.

3.6. Country-level variables

Institutional Quality Index (IQI). We control for institutional quality to capture the differences across countries. According to Ahlin et al. (2011) institutional quality influences MFI-level credit risk. Our measure of IQI is the sum of Kaufmann et al. (2010) Governance Indices: *Control of corruption; Government effectiveness; Political stability; Regulatory quality; Rule of law; and Voice and accountability*. Applying the composite IQI measure is consistent with previous studies such as Awaworyi Churchill (2019), Zamore et al. (2019).

Macroeconomy. It is evident in the literature that a country's macroeconomic condition influences MFI performance (Ahlin et al., 2011; Churchill, 2019). We particularly control for GDP per capita adjusted for international purchasing power parity (constant 2011) and GDP growth, both are retrieved from the World Bank. While the informal nature of MFIs allows them to thrive in poorer economies, those less wealthy nations are also more vulnerable because they are at the front-line of climate exposure with limited capacity to address the climate-related shocks (IPCC, 2013).

We also include a binary variable *CRISIS*, to control for the time effect of the global financial crisis (GFC). Our sample period runs from 1999-2019, while the GFC took place between 2007-2009. The loan portfolios of several financial institutions were severely impacted during the crisis, and MFIs faced similar risks. Following Zamore et al. (2019), we include an indicator variable that takes a value of 1 for the period 2007-2009, and 0 otherwise. Lastly, we control for regional differences by including *regional dummies*. MFIs in our sample are geographically positioned in East Asia and Pacific (EAP), Eastern Europe and Central Asia (EECA), Latin America and Caribbean (LAC), Sub-Saharan Africa (SSA), South Asia (SA), and Middle East and North Africa (MENA).

4. Methodology

4.1. Model specification

This study employs a dynamic panel model based on an unbalanced panel dataset. Several econometric issues in the literature are addressed by applying the GMM estimation while complying with the dynamic pattern of the dataset. This technique can resolve Nickell's (1981) finite-sample bias for a dynamic panel regression with the presence of firm fixed effects to give an unbiased estimator. Specifically, the GMM approach deals with possible endogeneity between MFI's performance and other covariates in our models that can lead to error or misinterpretation of regression findings. For example, geographic expansion is an endogenous decision and MFI expansion can be motivated by past credit risk. This issue can be resolved by using fixed/random effect or a traditional instrumental variable (IV) estimation. While the IV approach addresses endogeneity concerns arising from unobserved simultaneity and/or heterogeneity, it is not designed to address the dynamic nature of the relationship. Our baseline empirical model is given by Equation (1):

$$\boldsymbol{Risk_{ijt} = \gamma_i + \delta_t + \mu Risk_{ijt-1} + \beta_k MFI_{ijt}^{k} + \beta_m MACRO_{jt}^{m} + \emptyset CVUL_{jt} + \varepsilon_{ijt}} \tag{1}$$

$Risk_{ijt}$ denotes the credit risk of MFI i in country j at time t. The variables used to measure credit risk are (i) portfolio at risk >30days (PaR30); (ii) loan loss provisions (LLP); (iii) write-off ratio (WOR); (iv) combined credit risk (CCR); and (v) zCCR of CCR. $Risk_{ijt}$ is written as a function of its past year value ($Risk_{ijt-1}$), a vector of k MFI level variables reflecting the characteristics of each MFI including geographic expansion (*GEX*) measured by branch number, and a vector of m variables measuring the macroeconomic conditions for all MFIs (*MACRO*) in each country j, and climate vulnerability (*CVUL*). The MFI-specific fixed effect ($\boldsymbol{\gamma_i}$) controls for unobserved factors that do not change over time for each MFI, whereas $\boldsymbol{\delta_t}$ is the time fixed effect. ε_{ijt} is the error term.

4.2. Estimation method

Trying to explain credit risk using climate vulnerability and a set of explanatory variables including macroeconomic controls may suffer from endogeneity depending on how climate vulnerability is measured. As stated in Section 3.3, we use ND-GAIN as a measure of climate vulnerability (CVUL) compiled by the Notre-Dame Global Adaptation Initiative (ND-GAIN). ND-GAIN also reports a readiness index, which combines many economic indicators, increasing the likelihood of endogeneity problems. However, even the climate vulnerability index contains some measures, which are potentially correlated with macroeconomic variables. On the other hand, geographic expansion of MFI branches is an endogenous choice, hence expansion strategy can be affected by the prior year's credit risk.

To address the possible endogeneity bias in our models we employ the two-step system GMM developed by Arellano and Bover (1995) and Blundell and Bond (1998) with finite-sample corrected standard errors as proposed by Windmeijer (2005). Specially, we use lagged differences of the dependent variables as instruments in level equations in addition to lagged levels of dependent variables for equations in the first differences, as suggested by Baltagi (2013). The use of the GMM internal instruments mechanism addresses concerns about potential endogenous factors and produces consistent, unbiased and efficient estimators for dynamic panel regression. The literature suggested including the lagged first differences of the explanatory variables as instruments for the equation in levels and the lagged values of the explanatory variables in levels as instruments for the equation in differences (Arellano & Bover, 1995; Blundell & Bond, 1998). Lag variables can control emerging simultaneity and reverse causality in the models. Additionally, we utilize system GMM to absorb high persistency of governance data and minimize the small-sample bias. The GMM provides an unbiased estimator for the dynamic panel data model with the presence of MFI fixed effects.

Our GMM model addresses possible endogeneity between microfinance credit risk and other covariates which could influence the interpretation of the empirical results.

Furthermore, adequate post-diagnostic tests have also been performed. These include the second-order (i.e. the AR(2)) Arellano-Bond autocorrelation test to detect the serial correlation of the residuals in the differenced equation, the Hansen J-statistics test for the joint validity of the full instrument set, and the Difference-in-Hansen test for the validity of the subset of instruments.

5. Empirical Results

5.1. Descriptive statistics

Table 1 shows the descriptive statistics of the study variables. On average, 7 percent of the total loan portfolio is in arrears for more than 30 days, 2.5 percent of the portfolio has been written off as irrecoverable and over 7.5 percent is reserved in anticipation of future loan losses. Summing PaR30 and Write-off, the total actual credit risk is about 27 percent of the loan portfolio. The major, 66 percent of MFI in sample are mature (at least 8 years and older), has an average 49 branches, and holds US$15.5 million in total assets, of which 34 percent is financed by equity capital. Regarding lending methodology, 11 percent of the MFIs practice group lending and the rest practice individual lending. The mean climate vulnerability index is nearly 43 percent.

[INSERT TABLE 1 ABOUT HERE]

Concerning ownership structure, 46 percent of the MFIs are shareholder-owned (consisting of banks and nonbank financial institutions) and the rest are non-shareholder-owned MFIs (comprising non-governmental organizations and cooperatives and member-owned organizations). With respect to macroeconomic and institutional quality indicators, the annual GDP growth is about 5 percent on average and the mean governance index is -3.30. A higher governance index means a higher quality of governance structure in the country. The financial crisis period accounts for about 14 percent of the observations. Finally, 16 percent of the MFIs are located in East Asia and Pacific, 17 percent in Eastern Europe and Central Asia, 20 percent in Latin America and Caribbean, 28 percent in Africa, 16 percent in South Asia, and the rest in the Middle East and North Africa.

Appendix D reports the Pearson pairwise correlations coefficients and variance inflation factor (VIF) scores between the independent variables. Most of the correlations are significant at the 1 percent level. The MFI-level variables, climate vulnerability factors and country-level variables are found not to be highly correlated, with an exception. We find a positive correlation (0.83) between climate vulnerability and GDP per capita, however it is within the 0.90 threshold suggested by Hair (2009). The table also reports the VIF test scores for all independent variables are below 6 (Studenmund, 2014). These results indicate that the joint inclusion of these variables in unlikely to lead to multi-collinearity issues.

5.2. Microfinance credit risk

Table 2 reports the system GMM estimates of Equation (1) to test *Hypotheses 1a, 1b* and *Hypotheses 2a, 2b*.[12] We confirm the validity of the system GMM estimators by performing several post-estimation tests reported at the end of Table 2. First, we report a statistically insignificant AR(2) test which indicates that second-order autocorrelation is not present. Additionally, we also state high *p*-values of Hansen-J test and difference-in-Hansen test. These *p*-values confirm that both the full set and each sub-set of instruments in the models are valid.

The coefficient for climate vulnerability (CVUL) (measured by the ND-GAIN index) is positive and significant in Column 1 of Table 2. This implies that climate vulnerability is associated with an increase in MFI provision for loan impairment. This evidence is consistent

[12] As suggested by the study (Maddala & Wu, 1999), we perform pre-estimation tests that includes checking the non-stationary of data using Fisher test suggested by Maddala and Wu (1999), followed by a Durbin-Wu-Hausman (DWH) endogeneity test at the level equation. Earlier test confirms no unit root concerns in the dataset as the null of non-stationary is rejected at the 1% level for all variables used in the regression, while later test finds an endogenous relationship between microfinance credit risk measures and MFI-level covariates. Results of these pre-tests are untabulated but are available upon request.

with *Hypothesis 1a*. Considering the economic impact of this climate vulnerability, a one point increase in country exposure to climate vulnerability is associated with a 53% (0.533*100) increase in loan loss provision for MFI loan portfolios. The economic effect is quite marked, however, the operating nature of MFIs and their responsibility to serving the most vulnerable makes this consequence plausible. Overall, the evidence indicates that MFIs operating in countries with higher exposure to climate vulnerability are associated with increased credit risk. The finding supports the work by Möllmann et al. (2020) and Pelka et al. (2015) who investigate the effect of adverse weather on credit risk for agricultural MFI loan portfolios. Further, our result is also consistent with the country-level case study by Fenton et al. (2017b) who report that riverine floods affect the way microfinance borrowers use their credit, with a significant portion spent in non-productive activities defaulting to loan delinquency and over-indebtedness. Similarly, our study also complements Klomp (2018) who examines the impact of natural disasters on MFI risk. Columns 2 and 3 of Table 2 report no significant relationship between climate vulnerability and PaR30 or WOR, respectively. This can be explained by the absence of a *contemporaneous* response of PaR30 and WOR toward CVUL in the context of the dynamic model estimation.

Columns 1, 2, 4 and 5 of Table 2 report positive and significant coefficients for geographic expansion (GEX) (proxied by the number of branches). Consistent with *Hypothesis 2a*, MFI loan portfolio credit risk is related to geographical expansion. Examining the effect of one new branch expansion, LLP increases by 4.4% (0.044*100) and PaR30 increases by 1.4% (0.014*100). Overall, we find that MFIs that diversify across different regions will also bear an associated loan portfolio default risk. Our findings are consistent with Zamore et al. (2019) who reported positive significant associations for the same credit risk measures. Further, this result supports the proposition under the agency-based models of corporate expansion, that growth into new markets leads to information asymmetry, weak monitoring and rising complexity in governing subsidies contributing higher risk in microfinance loan portfolios (Deng & Elyasiani, 2008; Goetz et al., 2016; Zamore et al., 2019). Overall we report that geographic expansion is associated with higher default risk which supports *Hypothesis 2a*.

[INSERT TABLE 2 ABOUT HERE]

Next we examine the interaction of climate vulnerability and geographic expansion on microfinance credit risk. The interaction coefficients, IVE, reported in Columns 1, 2, 4 and 5 of Table 2 are negative and significant, indicating that climate vulnerability moderates the consequences of geographic expansion on MFI loan portfolio credit risk. The result implies that MFIs assess location exposure to climate vulnerability as part of a branch expansion strategy. MFIs may choose not to geographically expand, or they may select a climate resilient area, resulting in lower credit risk. This suggests that climate vulnerability moderates the consequences of strategic expansion in the microfinance industry. In short, MFIs avoid locations that are exposed to climate risk. This finding also has implications for MFI mission drift concern. The MFI social mission is anchored on welfarist logic,[13] so that providing a financial service to the individual is key to the MFI objective. However, MFI expansion into climate prone regions may be compromised by a preference to avoid credit risk, overshadowing the microfinance mission to provide banking services to the poorest. The IVE coefficients support H3. Climate vulnerability moderates the consequences of geographic expansion on microfinance credit risk. Our empirical evidence complements the earlier findings of limited spatial accessibility in climate prone locations by Khan and Rabbani (2015) and Johnson et al. (2019). Our finding contributes to one of the research suggestions by Johnson et al. (2019) which was to better understand climate vulnerability from an MFI perspective.

[13] MFI that follows welfarist logic emphasizes more on depth of outreach and explicit in their focus on immediately improving the well-being of the vulnerable poor (Woller et al., 1999).

Table 2 also shows that the MFI and year fixed effects capture a significant fraction of overall explanatory power of three key credit risk measures; LLP, PaR30, and WOR. The SIZE coefficients report mixed results. The SIZE coefficients are positive and significant for LLP and WOR, but negative for PaR30. The positive association implies that credit risk increases with MFI size. This is plausible since large MFIs may be more competitive and aggressive in acquiring a higher market share of loan disbursements to risky clients. The negative association is consistent with Zamore et al. (2019) who report that large MFIs have fewer nonperforming loans. Large MFIs typically have better governance and monitoring within branches to limit default risk (Baele et al., 2007).

The equity capital (EC) MFI-level variable reports a marginally significant negative association with LLP, CCR, and zCCR, for columns 1, 4, and 5 of Table 2. The result suggests that greater MFI equity financing lowers default risk. Zamore et al. (2019), report a similar association for LLP using a single static model. MFIs avoid activities leading to default risk when there is a financing shortage (Zamore et al., 2019). Columns 2, 4 and 5 report a positive GROUP coefficient. Credit risk increases with more group lending. An increase in group lending can lead to more loan defaults. This evidence is contrary to prior microfinance research (Ghatak & Guinnane, 1999; Zamore et al., 2019). In particular, Zamore et al. (2019) report that group lending is significantly associated with lower default risk.[14]

The significant positive MATURE coefficient in column 2 indicates that older MFIs experience more defaults. Specifically, MFIs aged 8 years or older face higher nonperforming loans. Consistent with microfinance efficiency theory, MFIs become inefficient over time (Caudill et al., 2009). Zamore et al. (2019) document a similar outcome. Columns 3, 4 and 5 in

[14] Group lending is an innovative approach in the microfinance industry to address collateral and repayment issues (Armendáriz & Morduch, 2010).

Table 2 report significant positive coefficients for SHO meaning that credit risk is related to the proportion of MFI shareholder ownership. We discuss this further in section 5.3.

At the country level, the negative IQI coefficient given in Columns 1 and 3 of Table 2 suggests that a higher institutional quality index is associated with fewer nonperforming loans. This result is expected because good governance promotes transparency and integrity, and this is associated with a lower risk of default. Furthermore, our results also reveal that a country's economic conditions are negatively associated with microfinance credit risk. Specifically, the negative significant GDPg coefficients in Columns 1, 3, 4 and 5 demonstrate that positive economic growth lowers default risk. In general markers of healthy growing economies are consistent with financially healthy citizens. A result that is supported by the literature (Carey, 1998; Louzis et al., 2012; Zamore et al., 2019). The marginally significant negative GDPc coefficient in Column 1 of Table 2 shows that an increase in GDP per capita is associated with lower credit risk. Finally, the positive significant CRISIS coefficient in Columns 2, 4, and 5 shows that during the financial crisis MFIs were exposed to greater credit risk caused by the financial constraints. This result shows that default risk is not necessarily time-invariant. The finding is consistent with Zamore et al. (2019).

5.3. Microfinance credit risk: Ownership effects

We further explore the vulnerability-expansion-risk nexus for MFIs across ownership structures using subsamples. As discussed in section 3.5, many non-shareholder owned MFIs (microfinance NGOs, credit unions, cooperatives) struggle to monitor diversified branch networks and often lack good governance practice. These two shortcomings lead to greater default risk (Galema et al., 2012). Non-shareholder owned MFIs also focus more on social objectives. In contrast, shareholder-owned MFIs (banks, rural banks and non-bank MFIs) have adopted an institutionalist approach, that gives emphasis to financial sustainability and economies of scale. Shareholders are more concerned about governance and monitoring to minimize credit risk (Ko et al., 2019). These effects are examined more carefully in the subsample analysis reported in Table 3.

[INSERT TABLE 3 ABOUT HERE]

The positive significant CVUL and GEX coefficients in Columns 6 and 8 of Table 3 indicate that both climate vulnerability and geographic expansion are associated with credit risk for non-shareholder MFIs. From Column 8, a one point increase in country exposure to climate vulnerability is associated with a 37% (0.373*100) increase in the write-off ratio (WOR) and a one branch expansion increases the write-off ratio by 1.2% (0.012*100). Columns 1 and 2 of Table 3 show that climate vulnerability is not associated with microfinance credit risk for shareholder-owned MFIs, however geographic expansion (GEX) has a negative and significant association for LLP and PaR30. The evidence suggests that credit risk induced by climate vulnerability or geographic expansion is more pronounced for non-shareholder-owned MFIs. These results are consistent with the prior literature (Galema et al., 2012; Ko et al., 2019; Zamore et al., 2019).

In terms of MFI-level controls, SIZE reports a positive and significant coefficient in Column 1, so that large MFIs are associated with greater LLP for shareholder-owned MFIs.[15] The SIZE coefficient findings are similar to those in Table 2, however, the magnitude of the SIZE coefficient is much larger in Table 3. We also note that equity capital (EC) in Column 6, is associated with lower credit risk for the non-shareholder group. While it is well established that the financing of non-shareholder-owned MFIs (e.g., NGOs) primarily depends on subsidies (Hudon & Traca, 2011), this has been changing following concerns about MFI self-sufficiency. From Columns 1 and 3 of Table 3, group lending reduces the likelihood of default in shareholder-owned MFIs. Columns 1, 2, and 3 show more mature shareholder-owned MFIs are associated with greater credit risk.

[15] SIZE is only marginally significant for PaR30 in Column 7.

Regarding country-level control, Columns 1, 3, 4, and 5 of Table 3 report a strong negative relationship between GDP growth and risk for the shareholder-owned subsample. We also note that only shareholder-owned MFIs were exposed to greater credit risk during the global financial crisis given the significant positive CRISIS coefficients in Columns 2, 4, and 5.

IVES represents an interaction variable between climate vulnerability, geographic expansion and shareholder-owned MFIs. Columns 1, 4 and 5 of Table 4 report negative and significant IVES coefficients implying that shareholder-owned MFIs can reduce their credit risk in the face of climate vulnerability and geographic expansion. This finding suggests that better governance and monitoring practices of shareholder owned MFIs can reduce the likelihood of default risk due to geographic expansion and climate vulnerability (Galema et al., 2012; Zamore et al., 2019).

[INSERT TABLE 4 ABOUT HERE]

5.4. Robustness tests

We undertake two additional tests to verify the robustness of our findings. First, we employ two alternative credit risk measures (CCR and zCCR) that are used to estimate MFI credit risk. The estimated models with CCR and zCCR as dependent factors are reported in each of Tables 2 - 4. For most of the reported models, the CCR and zCCR coefficients mirror the statistical significance of LLP, PaR30, and WOR. Second, we use EM-DAT data as an alternative climate vulnerability measure. EM-DAT has been used in studies examining the economics of disasters (Noy, 2009; Klomp, 2014, 2018; Nguyen et al., 2020). We construct a climate-related disaster damage variable DAMAGE and use the measure for robustness checking. Table 5 reports the models estimated with DAMAGE and the interaction term IDE for credit risk measures, LLP, PaR30 and WOR. The findings are consistent with those reported in Table 1. The significant DAMAGE coefficient reported in columns 1, 2 and 3 shows that climatic disasters are positively associated with MFI credit risk. In terms of economic impact, a one point increase in DAMAGE is associated with credit risk increases of 27% (0.27.3*100), 13.5% (0.135*100) and 23% (0.233*100) for LLP, PaR30 and WOR, respectively. The positive significant GEX coefficients in Columns 2 and 3 show that geographical expansion carries a higher risk of credit default. One new branch expansion (GEX) is associated with increases of 0.5% (0.005*100) and 0.2% (0.002*100) for PaR30 and WOR, respectively. It is evident from columns 1, 2 and 3 that the interaction of DAMAGE and GEX, denoted by IDE, helps to moderate the consequence of geographic expansion on credit risk. The results confirm those reported in Table 1.

[INSERT TABLE 5 ABOUT HERE]

Regarding controls, Columns 1 and 3 of Table 5 show that credit default risk is positively related to both SIZE and EC. Similarly, a positive MATURE coefficient in Column 2 indicates that MFI default risk rises with MFI age. Conversely, the negative GROUP coefficients in Columns 1 and 3 show that group lending is negatively associated with credit risk. While the result is contrary to our earlier findings it is consistent with Zamore et al. (2019). The strong negative relationship between GDPg and credit risk, shown by the coefficients in Columns 1, 2 and 3 suggest that MFI credit risk is lower for countries with an increasing gross domestic product.

6. Conclusion

This study examines the impact of climate vulnerability and geographic expansion on credit risk of MFI loan portfolios. The existing empirical studies using data from the banking sector are inconclusive as to whether banks should diversify across regions, particularly in climate vulnerable areas. We extend the scope of the literature to include hybrid-banking organizations that have ‘double bottom’ line objectives. The purpose of this research is to investigate the effect of MFI expansion into areas subject to high risk of adverse climate shocks on their credit risk. In particular, we seek to better understand the impact of adverse climate shocks on MFI loan portfolios.

The key finding is that both climate vulnerability and geographic expansion both increase microfinance credit risk. The result is primarily driven by MFIs that are large, experienced and are not governed by shareholders. The findings remain robust when alternative measures of microfinance credit risk and a different climate-related dataset are used to estimate the models. Overall, the finding provides evidence of the negative effect of climate vulnerability and geographic expansion on MFI loan portfolio credit risk. With regard to the interaction effect, climate vulnerability helps to alleviate the consequence of geographic expansion on credit risk. In brief, MFIs avoid adverse climate exposed regions. The implied location shift also raises concerns about microfinance mission drift away from their social goals.

Additional results show shareholder-owned MFIs are more resilient to credit risk associated with climate vulnerability and geographical expansion. Hence these MFIs can successfully enter into new loan arrangements without compromising credit risk exposure. In contrast non-shareholder-owned MFIs experience greater credit default risk when they operate in climate vulnerable locations or expand into remote regions. Non-shareholder-owned MFI managers need to exercise caution when contemplating geographical expansion. For example, NGOs or member-run local cooperatives are crucial in coastal and remote areas for climate change adaptation and disaster management making them very vulnerable to climate-related disasters. Hence, these MFIs in particular may be affected by climate change risks. Our results suggest that both local and international efforts in the form of funds, technical assistance, or knowledge sharing are necessary for non-shareholder MFIs to simultaneously retain a local geographical presence and a positive impact. Given the expectation that climate change hazards will increase in frequency and severity (IPCC 2018) there is need to ensure the viability of non-shareholder-owned MFIs. The significance of the credit default risk relationship for non-shareholder owned

MFIs brings into question the commitment of shareholder-owned MFIs toward addressing climate change needs of their clients. This is an area that requires further investigation as it may mean funders and regulators of MFI’s may need to differentiate between non-shareholder and shareholder MFI’s when providing climate change risk assistance and monitoring.

Table 1. Descriptive statistics

The table reports descriptive statistics for the variables used in the empirical analysis. There are 15,042 MFI-year observations (2,591 MFIs) for twenty-one years covering 119 countries. All variables are defined in Appendix C. N is the number of observations. Mean, Std. Dev., Min and Max are the average, standard deviation, minimum and maximum values, respectively.

Variables	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Dependent variables					
LLP	12,770	7.64	388.22	-141.95	44,525.34
PaR30	15,042	7.35	15.20	0.00	711.43
WOR	3,454	2.48	23.48	-12.68	2,571.14
CCR	12,397	9.53	26.87	-2.86	2571.14
zCCR	3,454	0.00	1.00	-0.46	95.35
Independent variables					
CVUL	14,935	42.77	6.42	27.04	67.70
GEX	12,528	49.04	188.01	1.00	5,000.00
IVE	12,436	-68.50	1046.32	-30235.10	7204.41
IVES	11,504	7.09	491.64	-7604.41	12759.10
DAMAGE	9,936	17.40	2.781452	8.01	23.03
IDD	8,268	1058.50	3948.021	8.01	62,842.90
MFI-level controls					
SIZE	14,602	15.53	2.28	1.95	29.00
EC	14,581	0.34	1.21	-18.35	156.12
IND	3,409	-1,583.24	9064.14	-78,864.77	0.98
GROUP	15,042	0.11	0.32	0.00	1.00
SHO	13,938	0.46	0.50	0.00	1.00
MATURE	4,693	0.66	0.48	0.00	1.00
Country-level controls					
IQI	13,146	-3.30	2.63	-12.62	9.21
GDPc	15,000	7.192.87	6,283.11	630.68	62,526.94
GDPg	14,946	5.08	3.74	-46.08	54.16
CRISIS	15,042	0.14	0.35	0.00	1.00
Regional dummies					
AFRICA	15,031	0.28	0.45	0.00	1.00
EAP	15,031	0.16	0.37	0.00	1.00
EECA	15,031	0.17	0.38	0.00	1.00
LAC	15,031	0.20	0.40	0.00	1.00
MENA	15,031	0.03	0.16	0.00	1.00
SA	15,031	0.16	0.37	0.00	1.00

Table 2. Geographic expansion, climate vulnerability and credit risk

This table reports regression results for the effect of climate vulnerability and geographic expansion on MFI credit risk given by Equation (1). The dependent variable credit risk is measured by loan loss provision, portfolio at risk >30 days, write-off ratio, composite credit risk, and z-score of composite credit risk, respectively. Composite credit risk and its z-score are used as a robustness check. CVUL is climate vulnerability, GEX is geographic expansion, and IVE is the interaction of vulnerability and expansion measures. Variable definitions are given in Appendix C.

	(1)	(2)	(3)	(4)	(5)
	LLP	PaR30	WOR	CCR	zCCR
Lagged dep. (y_{t-1})	0.081***	0.485***	0.569***	0.337***	0.337***
	(0.006)	(0.022)	(0.018)	(0.024)	(0.024)
CVUL	0.533***	0.081	0.064	0.360	0.013
	(0.090)	(0.157)	(0.065)	(0.188)	(0.007)
GEX	0.044***	0.014***	-0.001	0.036***	0.001***
	(0.006)	(0.002)	(0.003)	(0.007)	(0.000)
IVE	-0.001***	-0.000***	-0.000	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SIZE	0.142*	-0.271*	0.185**	0.116	0.004
	(0.069)	(0.137)	(0.065)	(0.220)	(0.008)
EC	-1.349*	0.737	0.954	-4.147*	-0.154*
	(0.580)	(0.930)	(0.533)	(1.661)	(0.062)
GROUP	0.180	0.458**	-0.234	2.852***	0.106***
	(0.207)	(0.145)	(0.133)	(0.539)	(0.020)
SHO	0.493	0.062	0.524*	6.980***	0.260***
	(0.353)	(0.787)	(0.258)	(1.196)	(0.045)
MATURE	-0.147	1.434**	0.063	0.946	0.035
	(0.243)	(0.474)	(0.184)	(0.721)	(0.027)
IND	0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IQI	-0.677***	0.056	-0.272***	0.109	0.004
	(0.121)	(0.199)	(0.077)	(0.268)	(0.010)
GDPc	-0.000*	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDPg	-0.038*	-0.031	-0.045**	-0.232***	-0.009***
	(0.019)	(0.030)	(0.016)	(0.051)	(0.002)
CRISIS	0.176	0.603*	0.011	1.741***	0.065***
	(0.149)	(0.261)	(0.108)	(0.367)	(0.014)
CONSTANT	-28.428***	2.992	-7.297*	-19.908	-0.976*
	(4.340)	(7.498)	(3.318)	(10.472)	(0.389)
Observations	2,003	2,062	1,814	1,903	1,903
No. of MFIs	626	632	576	615	615
No. of Instruments	138	139	137	139	139
AR(1) test (*p*-value)	0.132	0.269	0.177	0.275	0.275
AR(2) test (*p*-value)	0.704	0.290	0.294	0.349	0.349
Hansen test (*p*-value)	0.302	0.752	0.530	0.887	0.887
Difference-in-Hansen (*p*-value)	0.440	0.626	0.828	0.481	0.481
Wald Chi^2 (*p*-value)	0.000	0.000	0.000	0.000	0.000

Table 3. Geographic expansion, climate vulnerability and credit risk for shareholder and non-shareholder owned MFIs

This table compares the effect of climate vulnerability and geographic expansion on MFI credit risk by MFI ownership structure. The dependent variables measuring credit risk are loan loss provision, portfolio at risk >30 days, write-off ratio, composite credit risk, and z-score of composite credit risk, respectively. Composite credit risk and its z-score are used as a robustness check. CVUL is climate vulnerability, GEX is geographic expansion, and IVE is the interaction of vulnerability and expansion measures. Variable definitions are given in Appendix C. Robust standard errors are reported in parenthesis. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	(1)	(1)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Shareholder-owned MFI					**Panel B: Non-shareholder-owned MFI**				
	LLP	PaR30	WOR	CCR	zCCR	LLP	PaR30	WOR	CCR	zCCR
Lagged dep. (y_{t-1})	0.357***	0.653***	0.522***	0.546***	0.546***	0.011	0.711***	0.527***	0.503***	0.503***
	(0.066)	(0.041)	(0.057)	(0.128)	(0.128)	(0.008)	(0.050)	(0.023)	(0.133)	(0.133)
GEX	-0.024***	-0.044***	-0.028	0.069	0.003	0.015*	-0.021	0.012**	-0.019	-0.001
	(0.005)	(0.003)	(0.017)	(0.074)	(0.003)	(0.009)	(0.015)	(0.005)	(0.015)	(0.001)
CVUL	-0.201	0.329	-0.199	0.429	0.016	1.139***	-1.308***	0.373*	0.170	0.006
	(0.164)	(0.247)	(0.166)	(0.842)	(0.031)	(0.336)	(0.436)	(0.196)	(1.010)	(0.038)
IVE	0.001***	0.001***	0.001	-0.001	-0.000	-0.000	0.001	-0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SIZE	0.377***	0.256	0.111	-0.423	-0.016	-0.196	0.610*	-0.080	0.201	0.007
	(0.099)	(0.156)	(0.095)	(0.410)	(0.015)	(0.251)	(0.343)	(0.157)	(0.872)	(0.032)
EC	0.807	0.794	1.954**	-4.164	-0.155	-5.456***	4.370***	-1.377	-7.733	-0.288
	(1.061)	(1.895)	(0.991)	(5.205)	(0.194)	(1.334)	(1.162)	(1.057)	(8.352)	(0.311)
GROUP	-0.720**	0.397	-0.636***	1.469	0.055	1.609*	0.172	0.271	-1.240	-0.046
	(0.307)	(0.389)	(0.235)	(2.163)	(0.081)	(0.933)	(0.622)	(0.294)	(1.606)	(0.060)
MATURE	0.493*	1.304*	0.631**	1.731	0.064	-0.964	-0.612	-0.705	-0.997	-0.037
	(0.265)	(0.708)	(0.252)	(1.478)	(0.055)	(0.685)	(0.751)	(0.427)	(2.427)	(0.090)
IND	-0.000	0.000***	0.000	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IQI	-0.013	-0.757**	0.210	0.034	0.001	-0.866***	0.868**	-0.095	-0.170	-0.006
	(0.182)	(0.348)	(0.190)	(1.013)	(0.038)	(0.310)	(0.372)	(0.165)	(1.066)	(0.040)
GDP_c	0.000	-0.000	0.000	-0.000	-0.000	-0.000**	0.001***	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP_g	-0.055**	-0.027	-0.058***	-0.294***	-0.011***	-0.000	0.023	-0.008	-0.103	-0.004
	(0.022)	(0.049)	(0.017)	(0.107)	(0.004)	(0.048)	(0.066)	(0.029)	(0.183)	(0.007)
CRISIS	0.015	0.836**	-0.171	1.719*	0.064*	0.650	-0.081	0.123	-0.551	-0.021
	(0.154)	(0.378)	(0.153)	(0.940)	(0.035)	(0.394)	(0.394)	(0.266)	(1.124)	(0.042)
CONSTANT	3.434	-21.634	8.525	-8.815	-0.489	-48.859**	52.306**	-14.590	-4.060	-0.327
	(7.951)	(12.925)	(8.873)	(15.843)	(0.587)	(16.247)	(20.422)	(8.889)	(57.257)	(2.156)
Observations	1,135	1,200	1,035	1,134	1,134	900	898	811	787	787
No. of MFIs	339	352	321	342	342	309	304	277	287	287
No. of Instruments	74	74	74	74	74	74	74	74	74	74
AR(1) test (*p*-value)	0.000	0.268	0.000	0.296	0.296	0.144	0.039	0.195	0.020	0.020
AR(2) test (*p*-value)	0.164	0.303	0.637	0.343	0.343	0.232	0.356	0.259	0.872	0.872
Hansen test (*p*-value)	0.731	0.447	0.454	0.260	0.260	0.980	0.665	0.859	0.374	0.374

Difference-in-Hansen (*p*-value)	0.768	0.337	0.446	0.171	0.171	0.851	0.566	0.772	0.258	0.258
Wald Chi^2 (*p*-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 4. Credit risk and MFI ownership interaction with geographic expansion, climate vulnerability

This table reports the effect of climate vulnerability and expansion on MFI credit risk including the interaction term IVES. The dependent variables measuring credit risk are loan loss provision, portfolio at risk >30 days, write-off ratio, composite credit risk, and z-score of composite credit risk, respectively. Composite credit risk and its z-score are used as a robustness check. CVUL is climate vulnerability, GEX is geographic expansion, and IVE is the interaction of climate vulnerability and geographic expansion. IVES is the interaction of vulnerability, expansion and shareholder-owned group. All variables are defined in Appendix C. Robust standard errors are reported in the parenthesis. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	LLP	PaR30	WOR	CCR	zCCR
Lagged dep. (y_{t-1})	0.066***	0.495***	0.560***	0.337***	0.337***
	(0.007)	(0.021)	(0.017)	(0.023)	(0.023)
GEX	-0.009***	0.013***	-0.000	-0.011	-0.000
	(0.002)	(0.002)	(0.004)	(0.008)	(0.000)
CVUL	-0.073**	0.184*	-0.111***	-0.124	-0.005
	(0.029)	(0.095)	(0.041)	(0.182)	(0.007)
IVE	0.000***	-0.000***	-0.000	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IVES	-0.000***	-0.000	0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SIZE	0.069	-0.245	0.131*	-0.241	-0.009
	(0.072)	(0.158)	(0.074)	(0.192)	(0.007)
EC	-1.393***	0.709	0.843*	-6.427***	-0.239***
	(0.488)	(0.961)	(0.488)	(1.574)	(0.059)
GROUP	0.260	0.509***	-0.111	2.807***	0.104***
	(0.176)	(0.138)	(0.101)	(0.514)	(0.019)
SHO	0.417	1.306**	-0.240	6.790***	0.253***
	(0.258)	(0.625)	(0.292)	(1.165)	(0.043)
MATURE	-0.019	2.024***	0.146	1.281*	0.048*
	(0.205)	(0.446)	(0.174)	(0.669)	(0.025)
IND	0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IQI	0.047	-0.034	-0.084	0.557**	0.021**
	(0.072)	(0.152)	(0.071)	(0.223)	(0.008)
GDPc	0.000*	-0.000**	0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDPg	-0.040**	-0.016	-0.024	-0.339***	-0.013***
	(0.016)	(0.029)	(0.015)	(0.047)	(0.002)
CRISIS	-0.049	0.806***	-0.112	1.133***	0.042***
	(0.101)	(0.209)	(0.098)	(0.361)	(0.013)
CONSTANT	3.123**	-2.501	2.164	12.710*	0.238
	(1.481)	(3.914)	(2.069)	(7.551)	(0.281)
Observations	2,003	2,062	1,814	1,903	1,903
No. of MFIs	626	632	576	615	615
No. of Instruments	136	137	135	137	137
AR(1) test (*p*-value)	0.133	0.267	0.182	0.278	0.278
AR(2) test (*p*-value)	0.773	0.287	0.305	0.355	0.355
Hansen test (*p*-value)	0.225	0.677	0.500	0.676	0.676
Difference-in-Hansen (*p*-value)	0.421	0.565	0.789	0.360	0.360
Wald Chi2 (*p*-value)	0.000	0.000	0.000	0.000	0.000

Table 5. Robustness check using DAMAGE to replace climate vulnerability

The table reports the effect of climate vulnerability and expansion on MFI credit risk, where the climate vulnerability variable, CVUL, is replaced by DAMAGE (economic losses of all climate-related events in one country in a given year/ a country's prior year's GDP) as a robustness check. The dependent variables measuring credit risk are loan loss provision, portfolio at risk >30 days, and write-off ratio. GEX is geographic expansion, and IVE is the interaction of vulnerability and expansion measures. All variables are defined in Appendix C. Robust standard errors are reported in the parenthesis. ***, **, and * marks indicate statistical significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)
	LLP	PaR30	WOR
Lagged dep. (y_{t-1})	0.055	0.286***	0.433***
	(0.033)	(0.016)	(0.020)
GEX	0.001	0.005***	0.002***
	(0.001)	(0.001)	(0.001)
DAMAGE	0.273***	0.135***	0.233***
	(0.022)	(0.029)	(0.015)
IDE	-0.070***	-0.040***	-0.002***
	(0.000)	(0.000)	(0.000)
SIZE	0.415***	-0.920***	0.324***
	(0.059)	(0.119)	(0.063)
EC	2.343***	-0.425	1.424**
	(0.655)	(1.307)	(0.579)
GROUP	-0.272**	1.710***	-0.703***
	(0.105)	(0.213)	(0.118)
SHO	0.324	0.396	0.658***
	(0.210)	(0.521)	(0.162)
MATURE	0.185	1.546***	0.078
	(0.170)	(0.309)	(0.092)
IND	0.000***	-0.000	0.000
	(0.000)	(0.000)	(0.000)
IQI	0.012	-0.942***	-0.004
	(0.055)	(0.158)	(0.046)
GDPc	-0.000	0.000***	-0.000
	(0.000)	(0.000)	(0.000)
GDPg	-0.034**	-0.171***	-0.059***
	(0.017)	(0.025)	(0.009)
CRISIS	0.116	-1.402***	-0.406***
	(0.117)	(0.201)	(0.072)
CONSTANT	-11.167***	7.153***	-8.507***
	(1.143)	(2.468)	(1.203)
Observations	462	473	415
No. of MFIs	268	277	242
No. of Instruments	122	123	118
AR(1) test (*p*-value)	0.588	0.189	0.247
AR(2) test (*p*-value)	0.311	0.356	0.318
Hansen test (*p*-value)	0.774	0.867	0.734
Difference-in-Hansen (*p*-value)	0.792	0.760	0.306
Wald Chi2 (*p*-value)	0.000	0.000	0.000

7. Appendix A

Distribution of sample by country.

Country	No. of MFIs	Percent (%)	Cum. (%)
Afghanistan	19	0.73	0.73
Albania	6	0.23	0.96
Angola	2	0.08	1.04
Argentina	19	0.73	1.78
Armenia	16	0.62	2.39
Azerbaijan	38	1.47	3.86
Bangladesh	77	2.97	6.83
Belarus	2	0.08	6.91
Belize	1	0.04	6.95
Benin	31	1.20	8.14
Bhutan	1	0.04	8.18
Bolivia	27	1.04	9.22
Bosnia and Herzegovina	17	0.66	9.88
Brazil	48	1.85	11.73
Bulgaria	26	1.00	12.74
Burkina Faso	21	0.81	13.55
Burundi	19	0.73	14.28
Cambodia	22	0.85	15.13
Cameroon	27	1.04	16.17
Central African Republic	2	0.08	16.25
Chad	2	0.08	16.33
Chile	7	0.27	16.60
China	56	2.16	18.76
Colombia	46	1.78	20.53
Comoros	3	0.12	20.65
Congo, Dem. Rep.	26	1.00	21.65
Congo, Rep.	5	0.19	21.84
Costa Rica	18	0.69	22.54
Cote d'Ivoire	21	0.81	23.35
Croatia	2	0.08	23.43
Dominican Republic	19	0.73	24.16
Ecuador	72	2.78	26.94
Egypt, Arab Rep.	15	0.58	27.52
El Salvador	19	0.73	28.25
Eswatini	1	0.04	28.29
Ethiopia	23	0.89	29.18
Fiji	1	0.04	29.22
Gabon	1	0.04	29.26
Gambia, The	2	0.08	29.33
Georgia	18	0.69	30.03
Ghana	69	2.66	32.69
Grenada	1	0.04	32.73
Guatemala	27	1.04	33.77
Guinea	7	0.27	34.04
Guinea-Bissau	3	0.12	34.16
Guyana	1	0.04	34.20
Haiti	8	0.31	34.50
Honduras	28	1.08	35.58
Hungary	1	0.04	35.62
India	217	8.38	44.00
Indonesia	70	2.70	46.70
Iraq	12	0.46	47.16
Jamaica	6	0.23	47.39
Jordan	9	0.35	47.74
Kazakhstan	42	1.62	49.36

Kenya	39	1.51	50.87
Kosovo	12	0.46	51.33
Kyrgyz Republic	38	1.47	52.80
Lao PDR	30	1.16	53.96
Lebanon	6	0.23	54.19
Liberia	4	0.15	54.34
Madagascar	18	0.69	55.04
Malawi	10	0.39	55.42
Malaysia	1	0.04	55.46
Mali	19	0.73	56.19
Mexico	111	4.28	60.48
Moldova	11	0.42	60.90
Mongolia	13	0.50	61.40
Montenegro	4	0.15	61.56
Morocco	11	0.42	61.98
Mozambique	11	0.42	62.41
Myanmar	15	0.58	62.99
Namibia	2	0.08	63.06
Nepal	44	1.70	64.76
Nicaragua	36	1.39	66.15
Niger	18	0.69	66.85
Nigeria	69	2.66	69.51
North Macedonia	4	0.15	69.66
Pakistan	52	2.01	71.67
Panama	8	0.31	71.98
Papua New Guinea	9	0.35	72.33
Paraguay	6	0.23	72.56
Peru	75	2.89	75.45
Philippines	112	4.32	79.78
Poland	4	0.15	79.93
Romania	8	0.31	80.24
Russian Federation	126	4.86	85.10
Rwanda	44	1.70	86.80
Samoa	1	0.04	86.84
Senegal	29	1.12	87.96
Serbia	4	0.15	88.11
Sierra Leone	12	0.46	88.58
Slovak Republic	1	0.04	88.61
Solomon Islands	1	0.04	88.65
South Africa	15	0.58	89.23
Sri Lanka	26	1.00	90.24
St. Lucia	2	0.08	90.31
Sudan	1	0.04	90.35
Suriname	2	0.08	90.43
Syrian Arab Republic	3	0.12	90.54
Tajikistan	56	2.16	92.71
Tanzania	22	0.85	93.55
Thailand	1	0.04	93.59
Timor-Leste	3	0.12	93.71
Togo	18	0.69	94.40
Tonga	1	0.04	94.44
Trinidad and Tobago	3	0.12	94.56
Tunisia	1	0.04	94.60
Turkey	2	0.08	94.67
Uganda	26	1.00	95.68
Ukraine	3	0.12	95.79
Uruguay	2	0.08	95.87
Uzbekistan	33	1.27	97.14
Venezuela, RB	2	0.08	97.22
Vietnam	38	1.47	98.69

West Bank and Gaza	9	0.35	99.04
Yemen, Rep.	10	0.39	99.42
Zambia	8	0.31	99.73
Zimbabwe	7	0.27	100.00
Total	2,591	100.00	

8. Appendix B

Measures for the Notre Dame vulnerability and readiness indices.

Sector	Indicators	
ND-GAIN vulnerability index		
Food	1 Projected change of cereal yields	4 Rural population
	2 Projected population change	5 Agriculture capacity
	3 Food import dependency	6 Child malnutrition
Water	1 Projected change of annual runoff	4 Water dependency ratio
	2 Projected change of annual groundwater recharge	5 Dam capacity
	3 Fresh water withdrawal rate	6 Access to reliable drinking water
Health	1 Projected change of deaths from climate induced diseases	4 Slum population
	2 Projected change in vector-borne diseases	5 Medical staff
	3 Dependency on external resource for health services	6 Access to improved sanitation facilities
Ecosystems	1 Projected change of biome distribution	4 Ecological footprint
	2 Projected change of marine biodiversity	5 Protected biome
	3 Natural capital dependency	6 Engagement in international environmental conventions
Habitat	1 Projected change of warm periods	4 Age dependency ratio
	2 Projected change of flood hazard	5 Quality of trade and transport infrastructure
	3 Urban concentration	6 Paved roads
Infrastructure	1 Projected change of hydropower generation capacity	4 Population living under 5 m above sea level
	2 Projected change of sea level rise impacts	5 Electricity access
	3 Dependency on imported energy	6 Disaster preparedness
ND-GAIN readiness index		
Economic	1. Doing business	
Social	1. Social inequality	3. Education
	2. ICT infrastructure	4. Innovation
Governance	1. Political stability and non-violence	3. Rule of law
	2. Control of corruption	4. Regulatory quality

9. Appendix C

List of variables, definition and sources.

Variables	Definition	Sources
Dependent variables		
LLP	Loan Loss Provisions: A portion of loan portfolio reserved for future loan losses (%)	MIX
PaR30	Portfolio at risk >30 days: A portion of loan portfolio in arrears for more than 30 days (%)	MIX
WOR	Write-off ratio: A portion of loan portfolio written off and accounted as loss (%)	MIX
CCR	Composite risk metric calculated as the sum of PaR30 and WOR (%)	
zCCR	z-score of CCR: Calculate as the difference between composite credit risk (CCR) and its mean divided by its standard deviation.	
Independent variables		
CVUL	ND-GAIN climate vulnerability index.	ND-GAIN
GEX	Expansion across geography measured by the number of branches.	MIX
IVE	Interaction climate vulnerability and geographic expansion.	
IVES	Interaction of climate vulnerability, geographic expansion and shareholder-owned firm.	
DAMAGE	Economic damage caused by climatic disasters = Economic losses of all climate-related events in one country in a given year/ a country's prior year's GDP ($)	EM-DAT
IDE	Interaction of economic damage of climatic disasters and geographic expansion.	
MFI-level controls		
SIZE	Size of MFI measured by the natural logarithm of total assets.	MIX
EC	Equity capital = total equity/ total assets (%)	MIX
IND	Income diversification = non-interest income/ total assets (%)	MIX
GROUP	Dummy variable equal to 1 if the MFI uses group lending, 0 otherwise.	MIX
SHO	Dummy variable equal to 1 if the MFI owned by shareholder, 0 otherwise.	MIX
MATURE	Dummy variable equal to 1 if the MFI is aged 8 years or older, 0 otherwise.	MIX
Country-level controls		
IQI	Institutional quality index is measured by the sum of Kaufmann et al. (2010) Governance indicators (e.g., control of corruption; government effectiveness; political stability; regulatory quality; rule of law; and voice and accountability).	Kaufmann et al. (2010)
GDPc	Gross domestic product per capita, constant 2011 ($)	WDI-WB
GDPg	Growth rate of gross domestic product on annual basis (%)	WDI-WB
CRISIS	Dummy variable equal to 1 if the MFI operated during the global financial crisis period (2007-2009), 0 otherwise.	MIX
Regional dummies		
AFRICA	Dummy variable equal to 1 if the MFI is located in Africa region, 0 otherwise.	MIX
EAP	Dummy variable equal to 1 if the MFI is located in East Asia and Pacific region, 0 otherwise.	MIX
EECA	Dummy variable equal to 1 if the MFI is located in Eastern Europe and Central Asia region, 0 otherwise.	MIX
LAC	Dummy variable equal to 1 if the MFI is located in Latin America and Caribbean region, 0 otherwise.	MIX
MENA	Dummy variable equal to 1 if the MFI is located in Middle East and North Africa region, 0 otherwise.	MIX
SA	Dummy variable equal to 1 if the MFI is located in South Asia region, 0 otherwise.	MIX

10. Appendix D

This table reports the variance inflation factors and pairwise correlations for explanatory variables. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Variables	VIF	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) GEX	3.33	1.000															
(2) CVUL	3.93	-0.048***	1.000														
(3) IVE	2.53	-0.594***	-0.046***	1.000													
(4) IVES	1.30	0.359***	-0.047***	-0.516***	1.000												
(5) DAMAGE	1.07	-0.003	-0.007	0.009	0.003	1.000											
(6) IDE	2.53	-0.048***	0.004	0.000	0.107***	-0.583***	1.000										
(7) Size	1.24	0.355***	-0.012*	-0.113***	0.058***	0.006	-0.011	1.000									
(8) EC	1.18	-0.069***	0.007	-0.008	0.011	-0.006	0.010	-0.085***	1.000								
(9) IND	1.00	0.003	-0.005	-0.002	0.000	0.001	0.000	-0.014	0.001	1.000							
(10) Group	1.11	-0.002	0.055***	-0.004	-0.002	-0.009*	0.003	-0.002	0.025***	-0.010	1.000						
(11) SHO	1.17	-0.003	0.090***	0.017**	-0.064***	0.001	-0.031***	-0.025***	0.012*	0.007	0.043***	1.000					
(12) Mature	1.12	-0.046***	-0.008	-0.050***	-0.004	-0.012	0.073***	0.003	0.001	0.013	0.175***	-0.134***	1.000				
(13) IQI	1.57	-0.047***	0.474***	0.002	-0.049***	-0.013**	0.037***	-0.011	0.009	0.001	0.041***	-0.004	0.102***	1.000			
(14) GDPg	1.23	0.029***	-0.125***	-0.005	0.009	-0.006	-0.004	0.027***	0.005	-0.006	-0.041***	0.047***	-0.106***	-0.087***	1.000		
(15) GDPc	3.37	-0.050***	0.832***	-0.057***	-0.026***	-0.013***	0.010	-0.010	0.005	-0.018**	0.081***	0.075***	0.024***	0.367***	-0.228***	1.000	
(16) Crisis	1.12	0.014*	-0.017***	-0.009	-0.003	-0.011**	0.004	-0.035***	0.027***	0.005	0.029***	0.000	-0.045***	-0.022***	-0.002	-0.007*	1.000

11. References

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