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Climate Change in Microcredit Portfolios: Evidence on Vulnerability, Adaptation and Implications for Inclusive Finance

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ABSTRACT

Climate change poses new challenges to the social mission and financial viability of microfinance institutions (MFIs). These include the vulnerability of borrowers, increased credit risks and the need to adapt to the changing climate. Using a novel microcredit data set, we first study the prevalence of climatic hazards and vulnerabilities in the portfolios of MFIs across Latin America and the Caribbean as well as sub-Saharan Africa. We find evidence of microborrower vulnerability to climatic hazards and associated heightened credit risk. We then explore ecosystem-based adaptation (EbA) as a potential strategic complement to inclusive finance in aiding adaptation. Our analysis finds widespread autonomous implementation of EbA by agricultural microborrowers. While EbA measures appear to negatively moderate the association between climatic hazards and microborrower vulnerabilities, we do not find them to be directly associated with lower vulnerabilities. Furthermore, lenders do not appear to increase financing of adaptation in portfolios with greater exposure to climatic hazards. The findings suggest a need to enhance the effectiveness of adaptive actions and further potential to expand the financing of EbA by MFIs.

JEL Classification: G21, Q14, Q54

1 | Introduction

Climate change research highlights that low and middle-income countries as well as population groups such as smallholder farmers and the rural poor are particularly vulnerable (Morton 2007; Stern 2007; Heltberg et al. 2009; Bowen et al. 2012; Delaporte and Maurel 2018; IPCC 2022). This vulnerability stems from heightened exposure to climatic hazards and reliance on agriculture, which is particularly sensitive to changes in mean temperatures, increased weather variability and more frequent extreme weather events associated with climate change (Morton 2007; Stern 2007; Bowen et al. 2012; Delaporte and Maurel 2018; IPCC 2022), but also from adaptation deficits (Fankhauser and McDermott 2014). For these reasons, climate change poses a particular challenge for microfinance institutions (MFIs) serving rural areas and communities characterised by agriculture (Hammill et al. 2008; Agrawala and Carraro 2010). MFIs need to evolve their strategy to safeguard their social impact and maintain their financial sustainability. Against this background, we use a novel microcredit data set to study the prevalence of climatic hazards and vulnerabilities in the portfolios of such MFIs as well as the corresponding credit risk implications.

We also explore ecosystem-based adaptation (EbA) as a potential strategic complement to inclusive finance. Defined by the Convention on Biological Diversity (CBD) as 'the use of biodiversity and ecosystem services as part of an overall adaptation strategy to help people to adapt to the adverse effects of climate change' (Convention on Biological Diversity 2009), this form of adaptation has been recognised as a flexible and cost-effective adaptation option more accessible to disadvantaged groups than, for example, engineered options (Convention on Biological Diversity 2009; Colls et al. 2009; Jones et al. 2012; Munang et al. 2013; Vignola et al. 2015; IPCC 2022). It is therefore particularly promising in the context of agricultural microfinance.

The microfinance ecosystem is characterised by the relationship between MFI and the microcredit client (microborrower) at its heart, as well as several separate and shared stakeholders of both. In line with stakeholder theory, the organisational success of the MFI depends on meeting its obligations to its stakeholders (Freeman 1984). Besides its clients, these also include capital providers, regulators and local communities. Stakeholder expectations from an MFI have traditionally focused on social impact, specifically on poverty alleviation and economic development through financial inclusion. Over time, however, this has evolved into a triple bottom line of social, financial and environmental sustainability (e.g., Hall et al. 2008; Hammill et al. 2008; McKee 2008; Rippey 2009; Agrawala and Carraro 2010; Huybrechs et al. 2015). Fulfilment of these goals is largely determined by the social, financial and economic outcomes of the economic activities of microborrowers for which the MFI provides financing, in other words, in the mutual stakeholder relationship between the MFI and its microborrowers. It is also chiefly through this relationship that climatic hazards can affect the MFI. Conversely, the MFI can influence microborrower outcomes, for example, through lending and other services.

Tracking the effects of climatic hazards through this schematic stakeholder model of the microfinance ecosystem, which we develop in Section 2, we test several hypotheses derived from an extensive review of the existing research on climate change adaptation in agriculture, sustainable finance and microfinance, as well as organisational change. First, we examine the path from climatic hazards via microborrower vulnerability to MFI credit risk. Second, we attempt to shed light on the role of implementing and financing ecosystem-based adaptation in this context, as recent empirical research suggests that such practices are being widely used already (Burnham and Ma 2016; Harvey et al. 2017). Lastly, we consider potential drivers of the adoption and financing of such adaptive measures, given that lack of access to credit remains a frequently reported barrier to adaptation (Vignola et al. 2015; Castells-Quintana et al. 2018).

We test the hypotheses using a unique pre-intervention survey of MFI field staff on their environmental observations, client practices and portfolio characteristics. In doing so, we focus on agricultural activities, as these have been highlighted in the climate change and adaptation literature as particularly sensitive to climatic hazards. The data set contains around 1500 anonymised responses by MFI branch heads and field officers on their respective credit portfolios, covering institutions in 13 countries across Latin America and the Caribbean (LAC) and sub-Saharan Africa (SSA). We report key descriptive results of the survey and explore our hypotheses using several multivariate Poisson and fractional regression models.

In the microcredit portfolios covered by our survey, we find that borrowers are exposed to climate risks on a large scale and find evidence of the resulting vulnerabilities and credit risks. Our results show that microborrowers autonomously react to climate hazards by implementing adaptive actions. These are also partially financed by MFIs. While we do not find a direct association of these autonomous adaptations with lower borrower vulnerability and MFI credit risk, they appear to negatively moderate the association between climatic hazards and increased borrower vulnerability. In conjunction, these results suggest that microborrower vulnerability to climate change and resultant MFI risks warrant close attention. While there appears to be fertile ground and further potential to expand the financing of ecosystem-based adaptation, there is a need to enhance the effectiveness of adaptation measures for this to succeed as a vulnerability reduction strategy.

We contribute to the existing literature on sustainable and inclusive finance and on ecosystem-based adaptation in several novel ways: First, we introduce a new stakeholder ecosystem model of microfinance as a descriptive and instrumental framework for further research. Second, we add empirical evidence of the presence of climate change adaptation in MFI portfolios at the previously unstudied level of individual loan officers' portfolios. This gives us a more granular insight than high-level overviews examining entire MFI portfolios (e.g., Agrawala and Carraro 2010; Ahmed et al. 2022), and at the same time much wider geographical reach than existing case studies. Third, we are the first to report on the perceptions of MFI field staff regarding their smallholder farmer clients' vulnerability to climate variability and change, as well as the adaptation measures observed by field staff. Fourth, by establishing the link to portfolio credit risk, we provide empirical insight into the triple bottom line argument that facilitating client adaptation can be a strategy for MFIs to meet their social and environmental responsibilities towards their stakeholders while preserving their own financial sustainability in the face of climate change.

The remainder of this paper is structured as follows. The next section introduces our theoretical framework grounded in stakeholder theory and develops our hypotheses, drawing from research across strategic management, sustainable finance and climate change adaptation. The third section introduces the data employed as well as our empirical strategy. The descriptive and econometric evidence we obtain is presented in the fourth section. The fifth section offers a further discussion of the findings and potential limitations. In the final section, we draw conclusions and outline practical implications as well as avenues for further research.

2 | Theoretical Background and Hypotheses

To organise our exposition of the theory and the hypotheses that guide our empirical investigation, we introduce a stakeholder model. Since Freeman's (1984) foundational work, such models have been widely used in the strategic management literature and practice (Donaldson and Preston 1995; Jones and Wicks 1999; Post et al. 2002). Stakeholder theory adopts the relationships between a company and its stakeholders as the focus of analysis (Parmar et al. 2010), where stakeholders are typically defined as 'any group or individual who can affect or is affected by the achievement of the organisation's objectives' (Freeman 1984). The 'stakeholder view' understands the successful management of such relationships to critical stakeholders as the central task of strategic management and ultimate source of organisational success.

Stakeholder theory offers a particularly suitable analytical model in the context of microfinance. This is because microfinance was conceived in the 1970s with a view to the social impact on its stakeholders, that is, with an explicit double bottom line that contrasted with the conventional shareholder focus prevalent at the time. Subsequently, microfinance moved to a triple bottom line of social, financial and environmental sustainability (e.g., Hall et al. 2008; Hammill et al. 2008; McKee 2008; Rippey 2009; Agrawala and Carraro 2010; Huybrechts et al. 2015), giving rise to the notion of green microfinance or green inclusive finance. Both sustainability and stakeholder theory entail widening the perspective away from a narrow focus on shareholder value and emphasise longer term value creation (Hörisch et al. 2014). These commonalities are reflected by the widespread use of the stakeholder model in areas such as environmental management (e.g., Onkila 2011) and climate change (e.g., Lozano et al. 2015; Daddi et al. 2018).

Our model is presented in Figure 1. At its centre are a representative microfinance institution (MFI), its representative borrower and their mutual stakeholder relationship as the core of the microfinance ecosystem. This perspective differs from more traditional stakeholder models, which centre on a single firm and abstract from any relationships between its stakeholders. Our model is inspired by the ecosystem (Rowley 1997) and network (Corazza et al. 2024) approaches to stakeholder theory. It also reflects the emergent view in the literature that sustainability and climate change are complex problems requiring the cooperation of stakeholders beyond the boundaries of a single organisation (Elia et al. 2020).

Fanning out from the MFI lender–borrower relationship in the centre, we map individual and common stakeholders of the

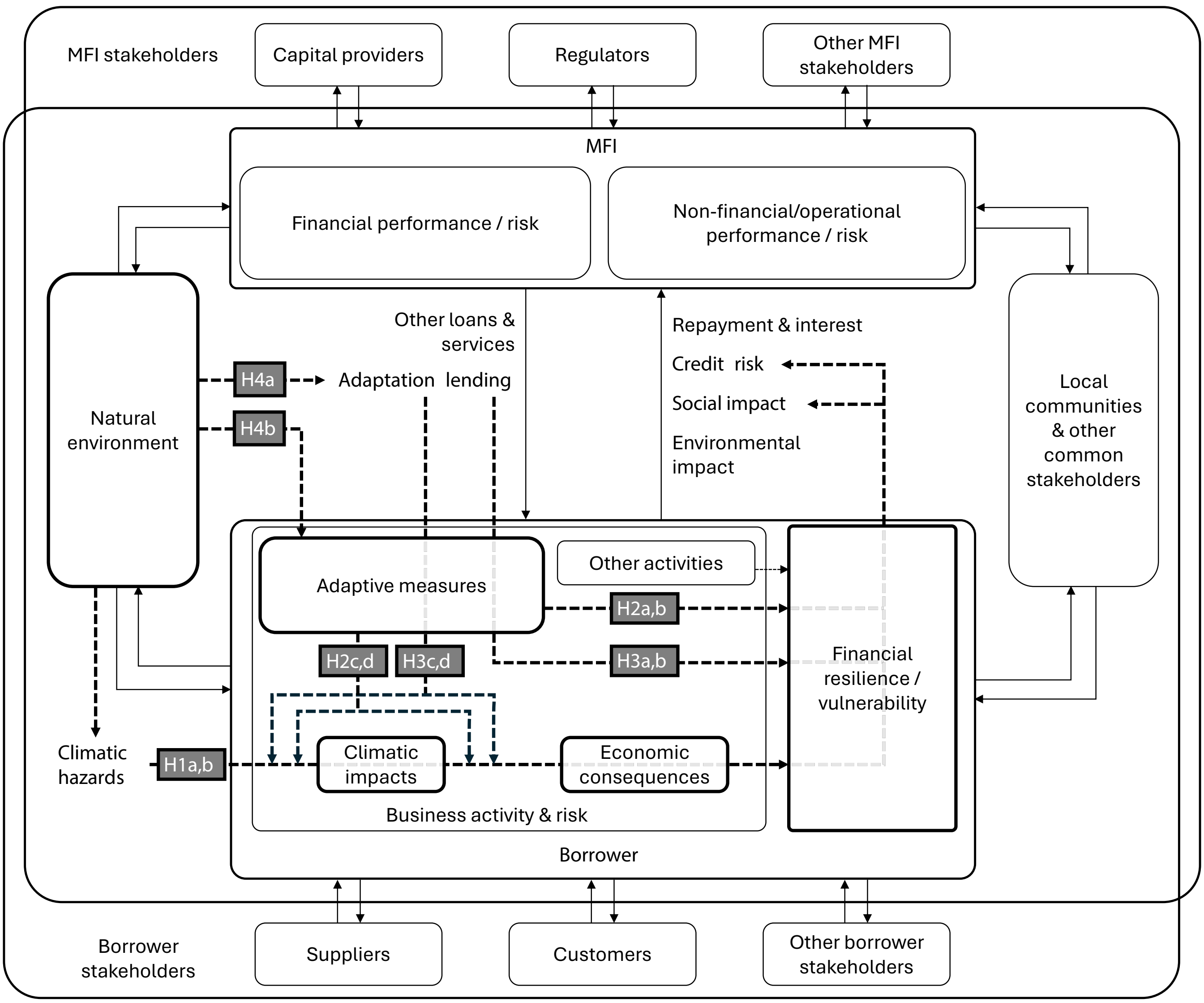

FIGURE 1 | Theoretical framework of MFI, borrower and respective stakeholders.

MFI and the borrower, focusing on organisational stakeholders (Henriques and Sadorsky 1999). Differing from the traditional stakeholder model, we also include the natural environment as a primary stakeholder, as proposed by Haigh and Griffiths (2009) particularly with a view to climate change. In the stakeholder relationship with nature, we focus on the role of climatic hazards for the microborrowers' business, but also acknowledge the potential for effects of the microborrower on the environment and a direct relationship between the MFI and the environment.

Jones and Wicks (1999) distinguish between descriptive, instrumental and normative uses of the stakeholder model. Our tailored model is descriptive in the sense of formalising our understanding of the microfinance ecosystem and critical interactions between selected stakeholders. In the following, we employ the theoretical framework in an instrumental way by posing several hypotheses regarding the effects of specific interactions between climatic hazards, the MFI and the microborrower.

2.1 | Microborrower and Adaptation

Following Hammill et al. (2008), we conceptualise the microborrower as a poor or vulnerable non-poor household that is economically active. Due to its economic activity, the household faces several stakeholders, including the MFI, and bears business risk from internal and external sources. The economic activity and associated risk, in turn, affect the household's overall financial situation, that is, its financial resilience or vulnerability.

Studies on the incidence of climate change vulnerability indicate that typical microfinance clients in developing countries, such as smallholder farmers and the rural poor, are particularly vulnerable to climate change. This is attributed to a combination of geographic exposure and sensitivity of their economic activities, undertaken primarily in the agricultural domain, to climatic hazards, such as heat extremes or changes in rainfall patterns (Stern 2007; Morton 2007; Heltberg et al. 2009; Agrawala and Carraro 2010; Bowen et al. 2012; Delaporte and Maurel 2018; IPCC 2022). Our framework (Figure 1) illustrates how climatic hazards can affect the business activity and risk of a microborrower, generating impacts on their assets and causing economic consequences, ultimately contributing to financial vulnerability.

Microborrowers can engage with the natural environment in several ways, including through resource depletion, degradation or mitigation efforts. However, our focus lies on their *adaptation* to climate change. This conforms with the recognition of microborrowers such as smallholder farmers as experienced agents of adaptation and managers of ecosystems in the human ecology literature (e.g., Cerdán et al. 2012). Recognising that adaptations are defined as measures that reduce vulnerability for a given level of exposure and sensitivity (Smit and Wandel 2006), we analyse the two potential effects of adaptation on microborrower vulnerability: direct effects as well as moderating effects on the relationship between climatic hazards and vulnerability mediated by the business activities of microborrowers.

Adaptation can be differentiated along several dimensions. Our focus is specifically on *autonomous* adoption of *ecosystem-based* adaptation (EbA) measures. *Autonomous* adaptation describes the existing, local adaptive capacity and practices of adaptation actors (Fankhauser et al. 1999). It forms the baseline for subsequent *planned* adaptation interventions, for example, by governments or development actors (Crane et al. 2011; Burnham and Ma 2016). EbA is a category of practices that utilise biodiversity and ecosystem services to facilitate adaptation to climate variability and change (Colls et al. 2009; Convention on Biological Diversity 2009). It is distinguished from other forms of adaptation such as behavioural, institutional or infrastructural adaptation (IPCC 2022). We focus on EbA because it is a form of adaptation more accessible to microenterprises than other options (Colls et al. 2009; Convention on Biological Diversity 2009; Vignola et al. 2015). Indeed, numerous studies document widespread autonomous use of EbA practices by smallholder farmers across developing countries (Burnham and Ma 2016). For instance, Harvey et al. (2017) provide evidence from surveying 300 smallholder farmers in Central America for 12 different EbA practices and find a mean of 3.8 EbA practices per farm. Similarly, a survey of 360 smallholders in Pakistan reports ten different EbA practices being used, with an average of 2.5 per farm (Shah et al. 2019). In both studies, the most common measures found include agroforestry practices, home gardens and contour planting.

2.2 | Microfinance Institution

The other central actor in our theoretical framework is the representative MFI. Besides the microcredit client, the key stakeholder in our context, its stakeholders include capital providers, regulators, the environment and local communities.[1] The triple bottom line approach of green microfinance implies that the MFI fulfils its responsibilities towards its stakeholders through financial performance, that is, adequately compensating stakeholders for their economic inputs, through social impact and through environmental responsibility.

The triple bottom line outcomes of the MFI are mediated by its business processes. In our framework, we represent these processes in a stylised manner as financial and operational risk-taking, abstracting for simplicity from the provision of ancillary services. While internal operations have social and environmental ramifications, the main social and environmental responsibilities of financial institutions derive from their financial intermediation activities (Cowton and Thompson 2000; De la Cuesta-González et al. 2006). In the case of an MFI, this relates to the welfare of microborrowers and any impact of their activities facilitated by the MFI.

2.3 | MFI-Borrower Interactions

The mutual stakeholder relationship between the MFI and its borrower consists of several related elements. In Figure 1, the most important of these elements are put as labels next to the two arrows indicating the stakeholder relationship. The MFI advances one or multiple loans to the borrower. These loans can be for general purposes or have a specific use of proceeds. For our analysis, we only distinguish between lending for ecosystem-based adaptation and lending for other purposes.

The main obligation for the microborrower associated with any loan is the payment of interest and principal. These cash flows are risky, with the credit risk being borne by the lender. Furthermore, the vulnerability of the microborrower and environmental effects of its business activity are also key determinants of the MFI's social and environmental performance. In sum, all three elements of the MFI triple bottom line are substantially determined in the stakeholder relationship with its microborrowers.

2.4 | Hypotheses

The dashed arrows in Figure 1 illustrate several potential cause–effect paths that emanate from climatic hazards posed by the natural environment. The first of these, labelled *H1a,b*, runs from climatic hazards to financial vulnerability to credit risk and social impact. It is based on the well-documented overlap between MFI activities and areas of heightened vulnerability to climate change (Agrawala and Carraro 2010; Moser et al. 2015; Forcella et al. 2016). Geographic exposure and sensitivity of economic activities, combined with insufficient adaptation actions, allow climatic hazards to generate physical impacts on the borrower's activities, for example, crop damage, reduced water availability or erosion. Such impacts, in turn, can have economic consequences to the microborrowers: increased unit cost, decreased unit income, increased cash flow variability or the loss of income sources. These adverse economic consequences ultimately reduce the borrower's financial resilience or, vice versa, increase their vulnerability. This proposed relationship between climatic hazards and microborrower vulnerability is our first subhypothesis:

Hypothesis 1a. *Climatic hazards faced by borrowers are associated with increased microborrower vulnerability.*

The second subhypothesis is the link to the MFI as a stakeholder in the microborrower, represented by the second leg of the dashed arrow *H1a,b* in Figure 1 from microborrower vulnerability to the microborrower-MFI relationship: The vulnerability of the microborrower affects the financial performance of the MFI through credit risk and, simultaneously, has implications for the social performance of the MFI.

This link between climatic hazards and lender performance has been acknowledged by banking supervisors (Financial Stability Board 2020; Basel Committee on Banking Supervision 2021) and corroborated by several recent contributions to the finance literature. In a simulation analysis, Dafermos et al. (2018) find that climate change is likely to increase the default rate of corporate loans by destroying the capital of firms and reducing their profitability and liquidity. Ascui and Cojoianu (2019) expand the literature on environmental credit risk management to include dependencies on natural capital that may introduce climate change vulnerabilities particularly of agricultural borrowers. On the empirical side, Klomp (2014) concludes that natural disasters, mainly due to the physical damage they cause, reduce the distance-to-default of commercial banks. Similarly, Albuquerque and Rajhi (2019) show that natural disasters lead to temporary increases in non-performing loans in developing countries.

Specifically in the microfinance literature, adverse effects of climate change on MFIs have been discussed at a theoretical level for some time (Hall et al. 2008; Forcella et al. 2017; Dowla 2018). The corresponding empirical evidence is more recent and still limited. The potential adverse effects of natural disasters on the solvency and liquidity of MFIs are demonstrated by Klomp (2018) using data on more than 1000 developing country MFIs. Collier et al. (2011) use data from a Peruvian MFI covering a period of a particularly severe El Niño event to illustrate the adverse effect of flooding on loan quality. Outside of natural disasters, three studies of microloans to smallholder rice farmers in Madagascar, each from a single MFI, demonstrate an association between the weather and vegetation health on the one hand and credit risk on the other (Pelka et al. 2015; von Negenborn et al. 2018; Möllmann et al. 2020). More systematic evidence on an association between climatic vulnerability and MFI credit risk is provided by Ahmed et al. (2022), albeit only at the country level.

We summarise these considerations on the implications for MFIs in the following subhypothesis:

Hypothesis 1b. *Climatic hazards faced by borrowers are associated with an increased portfolio credit risk.*

The focus of our study is on ecosystem-based adaptation measures, which include, for example, crop diversification and rotation, the use of organic fertiliser and agroforestry. Constructing a cohesive evidence base for the overall effectiveness of ecosystem-based adaptation (EbA) in addressing climate change vulnerabilities is challenging due to the diversity of applications, measures and targeted outcomes (Doswald et al. 2014; Milman and Jagannathan 2017; Chausson et al. 2020; Donatti et al. 2020). Nonetheless, the existing research results are broadly encouraging. Doswald et al. (2014) review 113 studies, including grey literature and peer-reviewed articles, focusing on EbA predominantly in the agricultural sector. These studies consider various climate hazards such as precipitation changes, temperature rises, storms and heatwaves, with impacts ranging from water scarcity and quality to flooding, biomass loss, and productivity decline. Among the peer-reviewed studies, 63% reported positive outcomes, while only 6% reported negative results of the EbA practices examined. Evidence for positive effects of specific EbA measures in agriculture, such as agroforestry (Vignola et al. 2015), crop diversification (Makate et al. 2016) and conservation agriculture (Thierfelder et al. 2017; Sardar et al. 2021), as well as of sustainable agricultural practices more generally, is provided in several more recent studies; benefits include increases in or reduced variability of productivity, income and food safety. These findings suggest that ecosystem-based adaptation can increase the financial resilience of microcredit borrowers:

Hypothesis 2a. *The implementation of EbA measures is associated with lower microborrower vulnerabilities to climate change.*

For MFIs as stakeholders in microborrowers, reductions in their vulnerability may materialise as lower credit risk:

Hypothesis 2b. *The implementation of EbA measures is associated with lower portfolio credit risk.*

In addition to these linear effects, which we depict as a dashed arrow labelled *H2a,b* from *Adaptive measures* via *Financial resilience/vulnerability* on to the microborrower—MFI stakeholder relationship in Figure 1, the findings in the literature discussed above also suggest a negative moderating effect of EbA measures. Concretely, adaptive actions undertaken by the microborrowers may reduce the impact of climatic hazards on microborrower vulnerability and, subsequently, credit risk. We formalise such potential moderating effects in the following two subhypotheses and illustrate them in Figure 1 with the dashed arrow *H2c,d* running from *Adaptive measures* to the path from *Climatic hazards* to *Financial resilience/vulnerability*.

Hypothesis 2c. *The impact of climatic hazards on the microborrower vulnerability is less pronounced with the implementation of EbA measures.*

Hypothesis 2d. *The impact of climatic hazards on the portfolio credit risk is less pronounced with the implementation of EbA measures.*

Since insufficient adaptation is seen as a key cause of heightened climate change vulnerability of lower-income countries (Fankhauser and McDermott 2014), an expansive body of literature examines contributing factors and barriers to adaptation and to EbA adoption specifically. In this line of research, access to credit/financial resources is identified as a key contributor to agricultural adaptation; conversely, credit constraints are found to be negatively associated with adaptive measures (Burnham and Ma 2016). The evidence base in this regard is particularly rich for agriculture in sub-Saharan countries (see, e.g., Deressa et al. 2011; Gebremariam and Tesfaye 2018; Makate et al. 2019; Ojo and Baiyegunhi 2020; Nyang'au et al. 2021), but the finding is also shown for regions in South Asia (Singh 2020; Sardar et al. 2021) and for livestock farming (García de Jalón et al. 2017). The apparent importance of access to finance for adaptation suggests that dedicated financing may empower the adoption of EbA measures. These measures, in turn, may reduce the vulnerability of microborrowers to climate change and lower their credit risk, in line with the extant evidence for the effectiveness of EbA and the hypotheses above.

However, to our knowledge, there are no studies that explicitly address the impact of adaptation lending on credit risk. Several existing studies examine the relationship between bank CSR in general and green lending in particular on the one hand and various aspects of bank performance on the other. Wu and Shen (2013), Cornett et al. (2016) and Bătae et al. (2021) all report an association of higher CSR with greater accounting profitability or lower non-performing exposures. Gangi et al. (2019) document that an increase in environmental activities is associated with an increase in the distance-to-default in an international sample of 142 banks. Similarly, Neitzert and Petras (2022) associate banks' CSR with lower bank default and portfolio credit risk and attribute this effect to the environmental engagement dimensions of CSR. By contrast, Khattak and Saiti (2021) do not find a clear association between bank environmental practices and their interest margins. Birindelli et al. (2022) report an inverse U-shaped relationship between banks' climate commitment and their credit risk, where stronger commitments are associated with lower credit risk for most of their sample. Ayayi and Wijesiri (2022) find that environmental performance adversely influences the financial performance of Asian MFIs. They identify the adoption of environmental policies and environmental risk assessments as the drivers of this negative effect; other dimensions of environmental engagement show no effect on financial sustainability.

The evidence regarding green lending specifically is limited and mixed. Nizam et al. (2019) find that in a large panel of 713 banks from 75 countries financing environmental impact is positively associated with return on equity. Zhou et al. (2022) report that in China, increased green lending is associated with a reduction in credit risk in the major state-controlled banks, but higher credit risk in local and regional banks. They attribute this result to differences in green lending expertise. Analysing the offering of green products and services as one dimension of environmental engagement, Ayayi and Wijesiri (2022) find it to not influence MFI financial performance. In their study of agricultural microcredit in Nicaragua, Dorfleitner et al. (2017) also distinguish different uses of proceeds. They find loans for the installation of irrigation systems, which can be seen as an adaptive measure, to exhibit higher default rates than loans with other purposes.

In sum, despite the good evidence for the effectiveness of EbA measures *per se*, the existing evidence on green and adaptation lending in microfinance contexts is mixed. Financing appears to be a relevant barrier to EbA adoption, but it is an open empirical question if the financing of EbA can generate benefits for microborrowers and MFIs in the form of reduced climate change vulnerability and lower credit risk. Consequently, we test the following hypotheses on the linear effects of EbA financing:

Hypothesis 3a. *The financing of EbA measures is associated with lower microborrower vulnerabilities to climate change.*

Hypothesis 3b. *The financing of EbA measures is associated with lower MFI portfolio credit risk.*

Furthermore, consistent with our proposed hypotheses regarding the effects of the implementation of EbA measures, we test for moderating effects of EbA financing on the association between climatic hazards and the outcomes for microborrowers and MFIs:

Hypothesis 3c. *The impact of climatic hazards on the microborrower vulnerabilities is less pronounced with the financing of EbA measures.*

Hypothesis 3d. *The impact of climatic hazards on the portfolio credit risk is less pronounced with the financing of EbA measures.*

Our final two hypotheses concern the drivers of adaptation and of lending towards adaptation, again with a focus on EbA. They are represented by the dashed arrows labelled *H4a* and *H4b* in Figure 1. The adaptation literature surveyed above suggests that ecosystem-based adaptation is already widespread among smallholder farmers and thus presumably also among microcredit borrowers (e.g., Harvey et al. 2017). It highlights the autonomous adoption of such measures in particular (e.g., Burnham and Ma 2016). This raises the question if these measures are already being taken by microborrowers in response to present climatic hazards. Besides factors such as access to financial resources, technical assistance and accurate weather information (e.g., Burnham and Ma 2016), personal experience of extreme weather events and changes in the climate also feature prominently among the contributing factors to autonomous adaptation discussed in the literature (e.g., Tisch and Galbreath 2018; Nyang'au et al. 2021). This leads us to the following hypothesis:

Hypothesis 4a. *Prevalence of climatic hazards is associated with increased adoption of EbA measures.*

While the inclusive finance literature emphasises the potential of microfinancing adaptation (Rippey 2009; Agrawala and Carraro 2010; Scheyvens 2015; Dowla 2018), conclusive evidence on the lending response of MFIs to climatic hazards is missing. Existing empirical studies of MFIs point to internal and external barriers to adaptation financing such as a lack of tailored lending products (e.g., Allet 2017; Helwig et al. 2020). The theoretical (e.g., Linnenluecke et al. 2012; Mazutis and Eckardt 2017) and empirical (e.g., Tisch and Galbreath 2018; Todaro et al. 2021) organisational change literature, however, posits that decision-makers' perception and sense-making of extreme weather events and climate change play a key role in determining responses to climate change such as adaptation.

Analogous to Hypothesis 4a and in line with the theoretical literature, we seek to provide relevant empirical evidence on the financing of adaptation by MFIs by testing the following final hypothesis:

Hypothesis 4b. *Prevalence of climatic hazards is associated with increased financing of EbA measures.*

3 | Data and Methodology

3.1 | Survey

Our empirical work is based primarily on an anonymised survey data set ('the survey') provided by YAPU Solutions, a provider of software and consulting services for microcredit applications. Between February 2019 and April 2021, the survey was delivered to MFIs newly included in four green inclusive finance projects entailing targeted capacity-building and the introduction of dedicated EbA financing products (denoted A, B, C and D in the following). Responses were collected at the assessment stage of each project, prior to any intervention. Hence, the results are not distorted by project interventions and can be interpreted as the baseline of adaptation adopted autonomously by borrowers and financed by MFIs.

The survey was administered through SurveyMonkey in Spanish and French and presented to MFI branch heads and field officers. The data set is unique in its granularity: Responses reflect field officers' observations and their local credit portfolios, rather than relating to the portfolio of the entire MFI. However, MFIs were asked to ensure a participation rate of 20% or more, so that cumulatively, the survey can be expected to cover a significant share of each MFI's total portfolio. After removal of incomplete, invalid, duplicate and implausible responses, around 1500 valid responses covering institutions in 13 countries across LAC and SSA remain.2 Project B accounts for 44%, project D for 36%, project A for 15% and project C for 4% of all responses. Ninety-two percent of responses come from the LAC region and 8% from SSA. All responses except those from project A are grouped by MFI. In specifications with MFI fixed effects estimator dummies, observations from project A are hence treated as coming from one MFI per country; they are omitted in specifications including MFI-specific variables. Questions relating to portfolio at risk and the share of portfolio financing EbA measures were only included in questionnaires used in projects B and D; hence, not every survey variable is available for each project and each country.

In Appendix S1, we present additional details on the survey. We include more information on the four projects and on the participating MFIs; it is shown that the participating MFIs are similar to the respective country medians across key characteristics. We also report the distribution of valid responses across projects and countries and present the questionnaire used.

3.2 | Variables

We compute two variables each for the reported climatic hazards as well as for reported impacts and economic consequences for borrowers: one count variable that simply aggregates the binary (Yes/No) answers and one intensity variable based on aggregating the Likert scale answers across the different phenomena.3 In our empirical analysis, we focus on the two variables for economic consequences to proxy microborrower vulnerabilities to climate change: the number of economic consequences reported (*#Consequences*) and their reported intensities (*Consequence_intensity*). Concerning the MFIs, we examine *PAR30* as a proxy for credit risk commonly used in the microfinance literature.

Regarding the use and financing of ecosystem-based adaptation measures, we construct count variables by counting the number of positive responses to an extensive list of different EbA measures. We also compute a score variable based on a catalogue of EbA measures compiled by the United Nations Environment Programm (UNEP) and Frankfurt School-UNEP Collaborating Centre for Climate & Sustainable Energy Finance (2014). They assign between 1 (lowest) and 3 (highest) points to each measure, reflecting the extent of impact reduction that can be expected from 40 different measures. To obtain the score for each response, we sum up these points over all measures reported as being used by clients for which the catalogue provides a rating.

In addition to the variable(s) of interest, we use four control variables in each regression: *Agri_share*, the share of each respondent's credit portfolio in agricultural activities, controls for differences in sensitivity of portfolios to effects of climate change due to their sectoral composition. Because agricultural activities are more sensitive to climatic influences than other economic activities, a greater exposure to this sector can be expected to entail greater impacts and consequences from climate change, as well as a potentially higher incidence of related repayment problems (Bastiaensen and Marchetti 2011; Dorfleitner et al. 2017; Castells-Quintana et al. 2018; Oostendorp et al. 2019). *Tenure (ln)* refers to the responding officer's log years of tenure at the MFI as a gauge of their experience and seniority. *ALSGNI* captures the average loan size in relation to each country's per capita income; this is a common control variable for loan size in the inclusive finance literature that can also be interpreted as a gauge for the depth of outreach (e.g., Dorfleitner et al. 2020). We control for potential differences due to macroeconomic circumstances with the variable *Growth*. In regressions with consequences or counts of EbA measures as explained variable, the control variable *#Credits (ln)* is used to control for the effect that the probability of observing a particular phenomenon or adaptation increases in the number of credits. In regressions with *PAR30* as explained variable, we also include *C19_measures* to control for effects of COVID-19–related measures on delinquencies as well as dummies for planting and harvesting seasons.

Two approaches are implemented to account for MFI idiosyncrasies: one set of regressions uses MFI fixed effects dummies; a second set of regressions combines country fixed effects dummies with four control variables capturing MFI characteristics. Including country dummies alongside MFI dummies is not feasible due to multicollinearity problems. Following the literature on MFI environmental performance (Allet and Hudon 2015; Forcella and Hudon 2016; Dorfleitner et al. 2020), we use the natural logarithm of total assets (*Assets (ln)*), the debt-to-equity ratio (*DTE*) and the operational self-sufficiency ratio (*OSS*) to control for the effects of MFI size, maturity and profitability, respectively. Furthermore, a categorical variable is used to distinguish between different charter types of MFIs. These are *Bank*, *Cooperative*, *Non-bank financial institutions* (NBFI), *Non-governmental organisation* (NGO) and *Others*. Table 1 presents descriptive statistics for all variables. Variable descriptions and data sources are provided in Table A1 and correlations in Table A2.

3.3 | Methodology

We examine our hypotheses using regression analysis, employing six different measures from the survey as dependent variables:

TABLE 1 | Descriptive statistics.

Variable	*N*	Projects	Countries	Mean	Median	Min	Max	St. dev.
Variables of interest								
#Hazards	1285	4	13	3.98	4.00	0.00	7.00	1.85
#Impacts	1136	4	13	6.87	7.00	0.00	14.00	3.99
#Consequences	1282	4	12	2.95	3.00	0.00	4.00	1.28
Hazard_intensity	802	4	11	2.71	2.50	0.00	7.00	1.33
Impact_intensity	720	4	11	4.16	4.00	0.00	12.50	2.81
Consequence_intensity	936	4	11	2.01	2.00	0.00	4.00	1.10
#EbA_used	1377	4	13	8.41	7.00	0.00	39.00	6.59
EbA_used_score	1377	4	13	17.38	15.00	0.00	73.00	12.73
#EbA_financed	1316	4	13	3.78	3.00	0.00	37.00	3.94
EbA_fin_score	1316	4	13	8.12	6.00	0.00	71.00	8.02
PAR30	813	2	6	0.04	0.03	0.00	0.37	0.05
EbA_share	585	2	6	0.09	0.00	0.00	1.00	0.22
Control variables								
Agri_share	1042	4	11	0.37	0.32	0.00	1.00	0.32
Tenure	1501	4	13	5.54	4.00	0.07	52.00	5.87
ALSGNI	994	4	11	0.80	0.47	0.00	12.43	1.14
#Credits (ln)	1032	4	11	5.63	5.66	0.00	10.00	1.23
Growth	1504	4	13	−1.43	0.01	−17.95	6.87	5.15
C19_measures	1505	4	13	28.64	0.00	0.00	100.00	35.39
MFI-level control variables								
Assets (ln)	28	3	9	18.19	18.20	14.13	21.17	1.58
DTE	28	3	9	4.63	4.37	0.50	13.23	2.48
OSS	28	3	9	1.14	1.14	0.78	1.46	0.15

Note: This table reports descriptive statistics for all available observations. For *Variables of interest* and *Control variables*, the number of observations *N* refers to survey responses. For *MFI-level control variables*, *N* is the number of MFIs for which each variable is observed. *Projects* and *Countries* indicate from how many projects and countries the observations *N* originate. Notably, *PAR30* and *EbA_share* were only surveyed in projects B and D; project C did not group responses by MFI, hence *MFI-level control variables* are only reported for three projects.

TABLE 2 | Mean number of different EbA measures used/financed, by country.

	#EbAs used		#EbAs financed	
	(1)	(2)	(3)	(4)
Country	*N*	Mean	*N*	Mean
Colombia	227	9.3	227	4.4
Costa Rica	23	10.7	18	5.7
Dominican Republic	62	10.5	62	6.1
Ecuador	608	6.2	589	2.7
El Salvador	178	10.5	171	4.3
Guatemala	60	13.2	60	7.1
Honduras	19	8.6	17	3.6
Nicaragua	58	12.9	50	5.4
Panama	22	16.0	18	6.4
Peru	23	8.2	8	1.0
LAC	**1281**	**8.5**	**1220**	**3.9**
Benin	20	7.2	20	3.1
Madagascar	36	8.9	36	1.7
Senegal	40	6.3	40	3.2
SSA	**96**	**7.4**	**96**	**2.6**
Total	1377	8.4	1316	3.8

Note: This table shows, by country, the average number of different ecosystem-based adaptation measures that respondents say their clients are using (Column 2), as well as the average number of different measures towards which respondents say they have granted credit (Column 4).

(1) *#Consequences* and (2) *Consequence_intensity* to proxy microborrower vulnerability, (3) *PAR30* as a measure of credit risk and (4) *#EbA_used*, (5) *#EbA_financed* as well as (6) *EbA_share* as proxies for the implementation or financing, respectively, of ecosystem-based adaptation measures. Considering their construction from lists presented to survey respondents, the use of count regression models is appropriate for (1), (2), (4) and (5). Due to its robustness to distributional misspecification, we use a Poisson model in all four instances. For the variables (3) and (6), we use fractional logit regression as both are fractions restricted to the unit interval (Papke and Wooldridge 1996). To not only examine linear associations, but also moderating and curvilinear effects, we augment selected regression models with interaction terms and (in Appendix S1) quadratic forms of explanatory variables of interest. In all regression settings, coefficient estimates are obtained using quasi-maximum likelihood (Wooldridge 2010). Heteroscedasticity- and cluster-robust standard errors are computed with countries and MFIs as clusters. To address the issue that the survey wording specifically asked to report hazards, impacts and economic consequences as observed *over the last three years*, we discuss results for the subset of respondents with *Tenure* of three or more years in Section 4.3. Such respondents can be expected to more accurately answer questions concerning this time-frame and have better knowledge of EbA practices adopted by their clients. The detailed regression tables for this subsample are presented in Appendix S1.

4 | Empirical Findings

4.1 | Descriptive Results on Climate Change and Ecosystem-Based Adaptation

96 percent of survey respondents report having observed at least one climate hazard over the past three years, with the mean and median respondents selecting four of seven different climate hazards surveyed. Of the 14 different impacts queried, respondents indicate an average of seven, which is also the median response. 94 percent of respondents report at least one impact of climatic hazards on their clients. Indirect impacts such as productivity losses as well as crop damage and losses are reported most frequently in both regions. Responses indicating none of the four economic consequences are infrequent; the mean respondent reports having observed three of four consequences for clients in the past three years, with a median of three. More detailed survey results are presented in Table A3. The high incidence of reports of climatic hazards, impacts and economic consequences in our survey is in line with Hypothesis 1a and the existing literature emphasising the vulnerability of typical microcredit clients. The results highlight the strategic challenge to MFIs posed by climate change and provide further motivation to study the effects on credit risk (Hypothesis 1b) as well as ecosystem-based adaptation as a potential mitigant.

The survey included 48 different EbA practices and asked the respondents (1) if these are used by their clients and (2) if they have granted credit to clients for their implementation. Table 2 provides summary results on the number of different measures reported. 95 percent and 99 percent of respondents in LAC and SSA, respectively, indicate at least one type of EbA as being used by their clients, with a mean of 8.5 and 7.4 and a median of 7 and 6.5, respectively. These findings illustrate that the autonomous adoption of EbA is widespread across all countries covered, in line with results in the adaptation literature (e.g., Burnham and Ma 2016; Harvey et al. 2017). This prompts us to further investigate their direct and moderating effects on vulnerability of microborrowers and credit risk (Hypothesis 2) as well as the drivers of their adoption (Hypothesis 4).

Regarding the financing of EbA, 85 percent and 91 percent of respondents in LAC and SSA, respectively, report that they provide financing for at least one of the surveyed adaptive measures. In LAC, the average respondent reports financing 3.9 different EbA measures (median of 3); in SSA, the mean is lower, at 2.6 (median of 2). Hence, the financing of adaptive practices appears to be not as prevalent as their usage in the portfolios represented in our survey. Information on the most frequently used and financed measures is presented in Tables A4–A6. The measures reported most often as being financed by respondents (Table A5) differ somewhat from those for which reported financing reaches the highest share of reported usage (Table A6). The highest rates of respondents indicating financing as a percentage of respondents indicating usage by clients are around 70percent in LAC and lower in SSA at around 65percent. In summary, there is considerable activity financing EbA measures even prior to interventions. Nonetheless, the differential between the number of different measures used by clients and the number financed, as well as the financing penetration rates reported, suggest that potential to increase dedicated financing of adaptive actions remains. We investigate if such financing indeed benefits MFIs by reducing credit risk (Hypothesis 3) and if climate hazards are already associated with increased financing of EbA measures (Hypothesis 4b).

4.2 | Multivariate Analysis

4.2.1 | Hypotheses 1a and 1b: Climatic Hazards, Vulnerability and Credit Risk

To assess Hypothesis 1a, we first use the number of economic consequences reported (*#Consequences*) and their reported intensities (*Consequence_intensity*) as dependent variables to proxy microborrower vulnerabilities to climate change. This also applies to the other hypotheses referencing microborrower vulnerabilities (Hypotheses 2a,2c,3a and 3c). In a second step, *PAR30* is used as the dependent variable to analyse credit risk effects as required by Hypothesis 1b and the subsequent Hypotheses 2b,2d,3b and 3d.

Table 3 presents the results of the Poisson regressions examining both measures of economic consequences to borrowers. Panels A and B of the table differ only in their measure of ecosystem-based adaptation, which we discuss further below in connection with the following groups of hypotheses. For the purpose of Hypothesis 1a, the variable of interest is, respectively, *#Hazards* in Columns 1–4 and *Hazard_intensity* in Columns 5–8. The control variables used are as described in Section 3.2. Considering the specifications without interaction terms between *#Hazards* and *EbA_used_score* in Panel A, we find a significantly positive association of climatic hazard reports with reports of economic consequences to borrowers. An additional hazard is associated on average with a 9–10 percent greater number of consequences reported (Columns 1 and 3), consistent across both strategies to account for variation between MFIs.4 The results using the intensity measures of hazards and consequences (Columns 5 and 7) are similar. Almost identical results for *#Hazards* and *Hazard_intensity* are obtained in Panel B of Table 3. Overall, these results provide support for Hypothesis 1a. Exposure to climatic hazards translates into an appreciably larger number and greater reported intensities of economic consequences to borrowers, such as increased cash flow variability.

To assess if the association between climatic hazards and economic consequences also carries over to portfolio credit risk as per Hypothesis 1b, we next estimate fractional logit regressions of the portfolio delinquency rate *PAR30* on our variables of interest and standard set of controls. The available sample is limited to responses from two of the four projects. The results are shown in Table 4. Again, Panel A includes *EbA_used_score* to account for implemented EbA measures, Panel B includes *EbA_fin_score* to assess the impact of financing EbA measures. We discuss the results for these variables in relation to hypothesis groups 2 and 3 below. In both panels, Columns 1 and 2 display results using *#Hazards* to capture climatic hazards, and Columns 3 and 4 use *Hazard_intensity* instead. No significant effect of *#Hazards* on *PAR30* is found, but increased *Hazard_intensity* is significantly associated with an increased *PAR30* across specifications. As the dependent variable *PAR30* can also be interpreted as the probability of delinquency of a dollar lent in the specific portfolio, an odds-ratio interpretation of the coefficient estimates is admissible (StataCorp 2019). The results imply increased odds of delinquency by approximately 1.07 if an additional hazard is reported with high compared to low intensity.

In sum, the regression models of *PAR30* provide limited evidence in favour of Hypothesis 1b. We find a significant association between *Hazard_intensity* and increased loan delinquencies in the surveyed portfolios, but the association is not significant when using the simpler count of reported hazards (*#Hazards*).

4.2.2 | Hypotheses 2a–2d: Effects of EbA Implementation

To shed light on Hypotheses 2a and 2b regarding the direct effects of EbA implementation on microborrower vulnerability and credit risk, we examine the findings for *EbA_used_score* in the same set of regressions of *#Consequences*, *Consequence_intensity* and *PAR30* as for Hypotheses 1a and 1b. As reported in Table 3, Panel A, *EbA_used_score* is significantly associated with more reports of consequences and also with higher reported intensities. While the effect size is small, this result appears to be at odds with the vulnerability-reducing effect of EbA reported in the adaptation literature and hypothesised in Hypothesis 2a.

To examine moderating effects of the use of EbA measures on the association between climatic hazards and microborrower vulnerabilities (Hypothesis 2c), we include an interaction term between the (demeaned) hazard variable and the (demeaned) *EbA_used_score* in columns 2, 4, 6 and 8 of Table 3, Panel A. This additional term receives a negative coefficient estimate throughout, significantly so in three of four specifications. Hence, the estimated partial effect of the hazard variable on the outcome variable measuring economic consequences becomes smaller for higher values of *EbA_used_score*. Untabulated computations of partial effects show that the estimated partial effect of *#Hazards* is no longer statistically different from zero for an *EbA_used_score* of 42–43 or higher (Columns 2 and 4). Analogously, the partial effect of *Hazard_intensity* (Columns 6 and 8) is no longer statistically different from zero for an *EbA_used_score* of around 50 and higher; this corresponds approximately to the top three percent of observed values for *EbA_used_score*. Overall, an increase of the hazard measure has a less pronounced effect on consequences if the given level of *EbA_used_score* is higher, as proposed in Hypothesis 2c.

For the connection to credit risk, we again turn to the regression results for the delinquency rate *PAR30* reported in Table 4. Across the four specifications in Panel A, no significant association between *EbA_used_score* and *PAR30* is detected; hence, Hypothesis 2b is not supported. To test for

TABLE 3 | Poisson regression: consequences.

Panel A

	#Consequences				*Consequence_intensity*			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
#Hazards	0.084***	0.087***	0.094***	0.096***				
	(0.012)	(0.010)	(0.012)	(0.008)				
Hazard_intensity					0.157***	0.165***	0.154***	0.160***
					(0.015)	(0.020)	(0.015)	(0.018)
EbA_used_score	0.003***	0.006***	0.003***	0.005***	0.005**	0.006***	0.005**	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
#Hazards_d ×		−0.003***		−0.003**				
EbA_used_score_d		(0.001)		(0.001)				
Hazard_int._d ×						−0.003*		−0.002
EbA_used_score_d						(0.001)		(0.001)
Agri_share	0.044	0.044	0.016	0.019	0.057	0.056	0.027	0.029
	(0.039)	(0.040)	(0.039)	(0.041)	(0.098)	(0.093)	(0.113)	(0.108)
Tenure (ln)	0.025	0.022	0.024	0.022	0.049**	0.044*	0.048**	0.044*
	(0.017)	(0.016)	(0.017)	(0.015)	(0.019)	(0.023)	(0.016)	(0.019)
ALSGNI	0.020*	0.020**	0.016	0.021	0.026	0.027	0.016	0.017
	(0.010)	(0.009)	(0.016)	(0.016)	(0.020)	(0.019)	(0.021)	(0.021)
Growth	0.003	0.002	−0.003	−0.005*	0.006	0.010*	−0.004	−0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.008)	(0.008)
#Credits (ln)	0.013	0.016	0.031	0.032	−0.001	0.006	0.022	0.027
	(0.024)	(0.023)	(0.023)	(0.022)	(0.034)	(0.038)	(0.024)	(0.026)
Assets (ln)			−0.008	−0.011			0.013	0.019
			(0.008)	(0.006)			(0.029)	(0.030)
DTE			−0.047***	−0.050***			−0.109***	−0.115***
			(0.006)	(0.005)			(0.011)	(0.012)
OSS			−2.174***	−2.045***			−1.712**	−1.826***
			(0.173)	(0.151)			(0.479)	(0.489)
Constant	0.599***	0.543***	3.086***	2.963***	0.001	−0.091	1.629*	1.595*
	(0.136)	(0.130)	(0.171)	(0.142)	(0.186)	(0.222)	(0.682)	(0.694)
MFI FE	Yes	Yes	No	No	Yes	Yes	No	No
Country FE	No	No	Yes	Yes	No	No	Yes	Yes
MFI type FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	775	775	675	675	510	510	441	441
R^2	0.401	0.416	0.408	0.423	0.300	0.308	0.293	0.298
Log-lik.	−1272.98	−1269.40	−1103.59	−1100.44	−753.28	−751.54	−655.23	−654.38

TABLE 3 | (Continued)

Panel B								
	#Consequences				***Consequence_intensity***			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
#Hazards	0.089***	0.093***	0.098***	0.101***				
	(0.013)	(0.011)	(0.013)	(0.010)				
Hazard_intensity					0.161***	0.169***	0.161***	0.166***
					(0.016)	(0.020)	(0.016)	(0.018)
EbA_fin_score	0.003***	0.008***	0.003***	0.007***	0.003*	0.006***	0.002	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
#Hazards_d ×		−0.004***		−0.004**				
EbA_fin_score_d		(0.001)		(0.001)				
Hazard_int._d ×						−0.006***		−0.004**
EbA_fin_score_d						(0.002)		(0.001)
Agri_share	0.044	0.047	0.017	0.024	0.082	0.080	0.047	0.046
	(0.037)	(0.037)	(0.036)	(0.038)	(0.101)	(0.097)	(0.116)	(0.113)
Tenure (ln)	0.025	0.023	0.024	0.022	0.049**	0.049**	0.049**	0.050**
	(0.017)	(0.017)	(0.017)	(0.018)	(0.020)	(0.022)	(0.017)	(0.018)
ALSGNI	0.019*	0.018*	0.015	0.018	0.021	0.022	0.014	0.016
	(0.010)	(0.009)	(0.016)	(0.015)	(0.015)	(0.015)	(0.017)	(0.017)
Growth	0.002	0.000	−0.004	−0.005*	0.007	0.007	−0.006	−0.006
	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)	(0.008)	(0.008)
#Credits (ln)	0.017	0.019	0.032	0.033	0.007	0.011	0.025	0.028
	(0.024)	(0.024)	(0.024)	(0.024)	(0.031)	(0.033)	(0.023)	(0.024)
Assets (ln)			−0.010	−0.012			0.011	0.013
			(0.006)	(0.006)			(0.030)	(0.030)
DTE			−0.048***	−0.055***			−0.113***	−0.117***
			(0.005)	(0.005)			(0.010)	(0.011)
OSS			−2.111***	−2.044***			−1.743***	−1.861***
			(0.158)	(0.146)			(0.423)	(0.445)
Constant	0.584***	0.533***	3.054***	2.983***	−0.006	−0.081	1.735**	1.794**
	(0.138)	(0.136)	(0.169)	(0.139)	(0.191)	(0.213)	(0.641)	(0.661)
MFI FE	Yes	Yes	No	No	Yes	Yes	No	No
Country FE	No	No	Yes	Yes	No	No	Yes	Yes
MFI type FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	761	761	669	669	501	501	437	437
R^2	0.403	0.417	0.411	0.426	0.286	0.296	0.275	0.281
Log-lik.	−1247.88	−1244.19	−1092.35	−1089.01	−741.48	−739.44	−651.16	−650.09

Note: Across Panels A and B, this table reports the results from Poisson regressions of *#Consequences*, the number of reported economic consequences for clients (Columns 1–4) and *Consequence_intensity*, the intensity score computed for the same list of consequences (Columns 5–8). In Panel A, *EbA_used_score* is included as a variable of interest; Panel B instead includes *EbA_fin_score*. Columns 2, 4, 6 and 8 include an interaction term between the relevant hazard and EbA variables in their demeaned form (suffix *_d*). Columns 1–2 and 5–6 use MFI fixed effects, while Columns 3–4 and 7–8 use country fixed effects, MFI-specific control variables, and fixed effects for the different charter types of MFIs. Detailed variable descriptions can be found in Table A1. Heteroscedasticity- and cluster-robust standard errors in parentheses. R^2 is computed as the squared correlation coefficient between actuals and predicted values (Wooldridge 2010).
*, ** and *** indicate a 10%, 5% and 1% level of significance, respectively.

moderating effects of EbA measures, we again include interaction terms between hazards and the EbA score in untabulated regressions, as done above for economic consequences. However, the coefficient estimates on the interactions are statistically indifferent from zero, providing no evidence in favour of Hypothesis 2d.

4.2.3 | Hypotheses 3a–3d: Effects of EbA Financing

Our analysis of the third group of hypotheses is analogous to the analysis above for the second group, but focuses on the effects of financing ecosystem-based adaptive measures, as proxied by *EbA_fin_score*. As reported in Panel B of Table 3, *EbA_fin_score* is significantly associated with more reports and a higher intensity of economic consequences. Similar to the results for *EbA_used_score*, we therefore reject the direct, vulnerability-reducing effect of EbA financing hypothesised in Hypothesis 3a.

Nonetheless, there is evidence in favour of a moderating effect of EbA financing: the interaction term between the (demeaned) hazard variable and the (demeaned) *EbA_fin_score* in columns 2, 4, 6 and 8 of Table 3, Panel B, receives a significantly negative coefficient estimate across specifications, supporting the moderating effect of EbA financing on the connection between hazards and vulnerabilities suggested in Hypothesis 3c. At an *EbA_fin_score* of 24 and above, the partial effect of *#Hazards* on economic consequences is no longer statistically positive (Panel B, Columns 2 and 4). When using *Hazard_intensity*, the positive association with *Consequence_intensity* ceases at an *EbA_fin_score* of around 30.

To examine the hypotheses on the relationship between EbA financing and credit risk, we turn to the regression results for the delinquency rate *PAR30* in Table 4, Panel B. Similar to the previous findings for *EbA_used_score*, no significant association between *EbA_fin_score* and *PAR30* is found. Furthermore, (untabulated) results for interaction terms between the pertinent climatic hazard variable and *EbA_fin_score* do not offer support for a moderating effect of EbA financing on the path from climatic hazards to MFI credit risk.

To briefly summarise the findings for the second and third groups of hypotheses: Our results do not show a *direct* relationship between the implementation or financing of EbA measures on the one hand and lower vulnerability of microborrowers or lower credit risk of MFIs on the other. Hence, we cannot confirm Hypotheses 2a,2b,3a and 3b. By contrast, our analysis of interaction terms and partial effects suggests that a higher level of ecosystem-based adaptation measures may dampen the adverse impact of climatic hazards on the economic outcomes of agricultural microborrowers. This finding of a negative moderating effect of EbA measures on the climatic hazards–economic consequences relationship supports Hypotheses 2c and 3c. Regarding credit risk, however, it appears that in our sample, the implementation and financing of ecosystem-based adaptations neither has a significant direct association with credit risk nor present themselves as significant moderating factors for the impact of climatic hazards. In this regard, Hypotheses 2d and 3d are also not supported.

In Appendix S1, we present additional tests for curvilinear effects of EbA measures and for moderating effects of EbA financing on the relationship between EbA implementation and microborrower/MFI outcomes. Overall, we do not find consistent evidence for the existence of such non-linear effects.

4.2.4 | Hypotheses 4a and 4b: Factors Associated With Ecosystem-Based Adaptation

Tables 5 and 6 present results for regression specifications examining which factors in our survey data are associated with the implementation and financing of ecosystem-based adaptation. The regressions of *#EbA_used* and *#EbA_financed* in Table 5 employ the Poisson model, while a fractional logit regression is used again for *EbA_share* in Table 6. Notably, data on *EbA_share* only comes from two of four projects, resulting in a smaller number of observations available.

The results show a significant association between *#Hazards* and the number of different EbA measures used by clients and financed by the respondents, as postulated in Hypotheses 4a and 4b. One additional reported hazard is associated with an increase in the number of different adaptations used of approximately 12 percent. However, when replacing *#Hazards* with *Hazard_intensity*, the association is only significant for *#EbA_used* (Hypothesis 4a).

Turning to *EbA_share* (Table 6), we do not find that field officers respond to the occurrence of different hazards by increasing the EbA lending share in their portfolios. This contradicts Hypothesis 4a and indicates that in the surveyed portfolios, the financing of ecosystem-based adaptations is not systematically used as a strategy to address climate change hazards.

Overall, the evidence on correlates of ecosystem-based adaptive measures supports Hypothesis 4a: the prevalence of climatic hazards appears to be associated with their increased *adoption*. There is also some support for Hypothesis 4b, increased *financing*, when considering *#EbA_financed*.

4.3 | Subsample Analysis and Further Robustness Checks

It is a concern that respondents may not be fully informed about EbA measures implemented by their clients or may not be aware of the occurrence and intensity of climatic hazards, impacts, and economic consequences. The survey wording specifically asked for observations *over the last three years*. Yet, the degree of information available to a respondent may vary based on their experience, client relationships, record-keeping, as well as procedures and policies of the MFI. Hence, we reproduce our regression models for the subset of responses with a *Tenure* of three or more years. Responses by these officers can be expected to be more accurate, due to greater familiarity with their area and better knowledge of their borrowers' activities. The corresponding results tables are presented in Section 5 of Appendix S1. This subsample analysis supports the previously presented findings. In particular, the association between economic consequences as dependent variable and hazards as explanatory variable is

TABLE 4 | Fractional logit regression of PAR30.

Panel A

	PAR30			
	(1)	**(2)**	**(3)**	**(4)**
#Hazards	−0.005	0.008		
	(0.013)	(0.013)		
Hazard_intensity			0.063***	0.067***
			(0.013)	(0.016)
EbA_used_score	−0.004	−0.003	−0.007	−0.006
	(0.003)	(0.003)	(0.004)	(0.005)
Agri_share	0.230*	0.255*	0.261	0.289*
	(0.113)	(0.118)	(0.154)	(0.139)
Tenure (ln)	0.063	0.031	0.033	0.012
	(0.056)	(0.054)	(0.060)	(0.063)
ALSGNI	−0.363*	−0.348**	−0.248**	−0.245**
	(0.147)	(0.131)	(0.081)	(0.079)
Growth	−0.074***	−0.049**	−0.044***	−0.069***
	(0.009)	(0.019)	(0.009)	(0.017)
C19_measures	0.010**	−0.009	−0.010*	−0.007
	(0.004)	(0.008)	(0.004)	(0.005)
Assets (ln)		−0.097		−0.081
		(0.075)		(0.068)
DTE		−0.188**		−0.276***
		(0.047)		(0.030)
OSS		−1.944**		1.016
		(0.642)		(1.012)
Constant	−2.633***	1.958*	−2.896***	−2.125
	(0.141)	(0.914)	(0.202)	(1.857)
MFI FE	Yes	No	Yes	No
Country FE	No	Yes	No	Yes
MFI type FE	No	Yes	No	Yes
Plant/Harvest FE	Yes	Yes	Yes	Yes
Observations	616	616	410	410
R^2	0.133	0.105	0.134	0.115

Panel B

	PAR30			
	(1)	**(2)**	**(3)**	**(4)**
#Hazards	−0.010	0.003		
	(0.011)	(0.012)		
Hazard_intensity			0.055**	0.060**

(Continues)

TABLE 4 | (Continued)

Panel B

	PAR30			
	(1)	**(2)**	**(3)**	**(4)**
			(0.015)	(0.019)
EbA_fin_score	−0.001	0.001	−0.002	−0.001
	(0.003)	(0.004)	(0.006)	(0.007)
Agri_share	0.216	0.237	0.228	0.255
	(0.111)	(0.119)	(0.154)	(0.140)
Tenure (ln)	0.058	0.026	0.021	0.000
	(0.057)	(0.054)	(0.063)	(0.065)
ALSGNI	−0.348*	−0.334**	−0.232**	−0.229**
	(0.136)	(0.121)	(0.074)	(0.071)
Growth	−0.073***	−0.049*	−0.043***	−0.067**
	(0.009)	(0.019)	(0.010)	(0.017)
C19_measures	0.011**	−0.008	−0.009*	−0.006
	(0.004)	(0.008)	(0.004)	(0.005)
Assets (ln)		−0.095		−0.068
		(0.075)		(0.067)
DTE		−0.188***		−0.274***
		(0.046)		(0.030)
OSS		−1.924**		1.080
		(0.644)		(0.972)
Constant	−2.685***	1.730	−2.989***	−2.631
	(0.119)	(0.913)	(0.170)	(1.772)
MFI FE	Yes	No	Yes	No
Country FE	No	Yes	No	Yes
MFI type FE	No	Yes	No	Yes
Plant/Harvest FE	Yes	Yes	Yes	Yes
Observations	611	611	407	407
R^2	0.131	0.103	0.126	0.109

Note: This table reports the results from fractional logit regressions of *PAR30*. In Panel A, *EbA_used_score* is included as a variable of interest; Panel B instead includes *EbA_fin_score*. Across both panels, Columns 1 and 2 use *#Hazards* to capture climatic hazards, and Columns 3 and 4 use *Hazard_intensity*. Columns 1 and 3 use MFI fixed effects, while Columns 2 and 4 use country fixed effects, MFI-specific control variables, and fixed effects for the different charter types of MFIs. Detailed variable descriptions can be found in Table A1. Heteroscedasticity- and cluster-robust standard errors in parentheses. R^2 is computed as the squared correlation coefficient between actuals and predicted values (Papke and Wooldridge 1996; Ramalho et al. 2011).
*, ** and *** indicate a 10%, 5% and 1% level of significance, respectively.

confirmed for counts and intensity measures (Hypothesis 1a). Regarding *PAR30*, the significantly positive coefficient estimates for *Hazard_intensity* are confirmed, while again no significant estimate for *#Hazards* results. The (negative) moderating effect of EbA measures on the relationship between climatic hazards and borrower vulnerability is confirmed (Hypotheses 2c and 3c), but again no linear vulnerability-reducing effect can be detected. A significantly negative effect of implemented adaptations on *PAR30* is found, but this does not occur when using *Hazard_intensity* instead of *#Hazards*. Interestingly, while the previous results for *#EbA_used* in Table 5 are confirmed, estimation in the restricted sample of respondents with three years or more of *Tenure* also shows a significant association of *#EbA_financed* with *Hazard_intensity*. This strengthens the evidence in favour Hypothesis 4b; however, for *EbA_share*, again no association with hazard measures is found.

TABLE 5 | Regressions of EbA use and financing.

	#EbA_used				*#EbA_financed*			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
#Hazards	0.120***	0.109***			0.106***	0.092***		
	(0.012)	(0.008)			(0.016)	(0.014)		
Hazard_intensity			0.104***	0.092***			0.080*	0.064
			(0.017)	(0.017)			(0.038)	(0.037)
Agri_share	0.180	0.199*	0.237	0.263	0.262*	0.298*	0.340	0.417
	(0.108)	(0.101)	(0.170)	(0.164)	(0.128)	(0.123)	(0.275)	(0.263)
Tenure (ln)	0.051	0.038	0.056	0.054	0.039	0.046	0.038	0.061
	(0.029)	(0.027)	(0.031)	(0.034)	(0.037)	(0.041)	(0.045)	(0.049)
ALSGNI	−0.041	−0.059	−0.075**	−0.057	−0.016	−0.021	−0.059	−0.033
	(0.024)	(0.033)	(0.028)	(0.040)	(0.030)	(0.047)	(0.042)	(0.053)
#Credits (ln)	0.026	0.020	0.030	0.007	0.104***	0.091**	0.091*	0.058
	(0.031)	(0.042)	(0.040)	(0.049)	(0.029)	(0.027)	(0.048)	(0.033)
Growth	−0.042***	−0.044***	−0.030***	−0.039***	−0.035***	−0.042***	−0.024***	−0.038***
	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.008)
Assets (ln)		−0.059*		−0.041		−0.010		−0.000
		(0.026)		(0.027)		(0.016)		(0.048)
DTE		−0.025		−0.050**		0.010		−0.013
		(0.015)		(0.019)		(0.022)		(0.026)
OSS		−0.141		−0.106		0.230		0.174
		(0.377)		(1.055)		(0.550)		(1.322)
Constant	1.548***	2.948***	1.760***	2.884*	0.351	0.438	0.707**	0.746
	(0.195)	(0.485)	(0.255)	(1.364)	(0.212)	(0.687)	(0.311)	(1.859)
MFI FE	Yes	No	Yes	No	Yes	No	Yes	No
Country FE	No	Yes	No	Yes	No	Yes	No	Yes
MFI type FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	788	686	534	459	774	680	524	455
R^2	0.206	0.186	0.146	0.116	0.157	0.150	0.122	0.116
Log-lik.	−2905.50	−2524.33	−2122.01	−1825.23	−2108.73	−1859.63	−1530.52	−1321.82

Note: This table reports results for Poisson regressions of *#EbA_used* and *#EbA_financed*. Columns 1, 3, 5 and 7 use MFI fixed effects, while Columns 2, 4, 6 and 8 use country fixed effects, MFI-specific control variables and fixed effects for the different charter types of MFIs. Detailed variable descriptions can be found in Table A1. Heteroscedasticity- and cluster-robust standard errors in parentheses. R^2 is computed as the squared correlation coefficient between actuals and predicted values (Wooldridge 2010).
*, ** and *** indicate a 10%, 5% and 1% level of significance, respectively.

As further robustness checks, we replace *EbA_used_score* with the simple count *#EbA_used* in the regressions of consequences and *PAR30*. We also re-run the regressions that use country dummies and MFI-specific variables as controls, replacing each MFI's *OSS* and *Assets (ln)* with return on assets (ROA) and the logarithm of its gross loan portfolio. In all instances, our findings remain the same so we refrain from reproducing detailed results in the interest of brevity.

5 | Discussion and Limitations

In several respects, our results from surveying MFI field officers are in line with climate change scholarship and with previous research in microfinance. Firstly, microborrowers are strongly affected by climatic hazards. Reports of various climatic impacts and economic consequences, as well as their strong association with hazard reports confirm the climate vulnerability of

TABLE 6 | Fractional logit regression of *EbA_share*.

	EbA_share			
	(1)	**(2)**	**(3)**	**(4)**
#Hazards	0.062	0.074		
	(0.068)	(0.059)		
Hazard_intensity			0.134	0.144
			(0.112)	(0.119)
Agri_share	2.777***	2.778***	3.169***	3.205***
	(0.216)	(0.216)	(0.176)	(0.154)
Tenure (ln)	0.103	0.111	0.136*	0.134*
	(0.054)	(0.055)	(0.058)	(0.056)
ALSGNI	−0.161	−0.184	−0.104	−0.116
	(0.262)	(0.290)	(0.249)	(0.265)
Growth	0.122***	0.057*	0.130***	0.037
	(0.013)	(0.024)	(0.013)	(0.038)
Assets (ln)		0.205*		−0.018
		(0.081)		(0.171)
DTE		0.012		0.097
		(0.052)		(0.085)
OSS		−3.609*		−4.350*
		(1.476)		(2.048)
Constant	−3.685***	−3.455	−3.896***	1.512
	(0.450)	(2.161)	(0.362)	(3.838)
MFI FE	Yes	No	Yes	No
Country FE	No	Yes	No	Yes
MFI type FE	No	Yes	No	Yes
Observations	480	480	330	330
R^2	0.188	0.185	0.254	0.253

Note: This table reports the results from fractional logit regressions of *EbA_share*. Columns 1 and 3 use MFI fixed effects, while Columns 2 and 4 use country fixed effects, MFI-specific control variables and fixed effects for the different charter types of MFIs. Detailed variable descriptions can be found in Table A1. Heteroscedasticity- and cluster-robust standard errors in parentheses. R^2 is computed as the squared correlation coefficient between actuals and predicted values (Papke and Wooldridge 1996; Ramalho et al. 2011).
*, ** and *** indicate a 10%, 5% and 1% level of significance, respectively.

microborrowers (Hypothesis 1a). Secondly, microborrowers and MFIs undertake and finance various adaptations on their own, even without targeted intervention; however, there appears to be additional potential to increase adaptation financing.

While these findings corroborate existing scholarship, they should be interpreted in the context in which the survey data was collected. The participating MFIs voluntarily chose to participate in projects aimed at the promotion of ecosystem-based adaptation; they generally represent a low proportion of the total MFIs in each country. In addition, we cannot exclude self-selection of bank staff into the survey. Due to these self-selection concerns at two levels, our survey results may not be representative for the relevant parent population of microcredit portfolios in the respective countries. For instance, project participation may be associated with an already higher level of familiarity with EbA at the MFIs or above-average climate change exposure in their portfolios. Mitigating factors to these concerns are the large regional footprint of the survey, the overall similarity of the included MFIs to regional medians reported in MIX Market across key parameters as presented in Section 2 of Appendix S1, and the presentation of the survey to field officers in cooperation with their employer as a part of their professional duties, with a request to each MFI to ensure at least 20 percent participation.

Our multivariate analysis of the novel portfolio-level data provides more granular evidence than existing MFI-level research and offers a new perspective by examining portfolio credit risk directly. Overall, we find strong evidence that climatic hazards are associated with economic problems for microborrowers and some evidence that such hazards entail increased credit risk (Hypothesis 1b), as the reported intensity of climatic hazards is associated with greater loan delinquencies (*PAR30*).

Our results on the effectiveness of ecosystem-based adaptation to counter these risks (Hypotheses 2a to 3d) are mixed. On the one hand, *EbA_used_score* as well as *EbA_fin_score* are associated with a slightly larger number of different economic consequences and greater intensity. This could indicate that the direct vulnerability-reducing effects of EbA are small and potentially masked by a signalling effect: EbA measures carry information on exposure beyond what the survey reports of climate hazards capture. Regarding credit risk, neither the use nor the financing of EbA measures is associated with a significantly lower *PAR30* in the full sample. A significant effect emerges when considering the *EbA_used_score* in the sample of respondents with greater tenure, which can be expected to be more knowledgeable of their portfolios and hence provide more accurate information. On the other hand, we find evidence for a negative moderating effect of EbA measures on the link between climatic hazards and microborrower vulnerabilities. A higher level of adaptation use or financing dampens the effects of the occurrence of an additional hazard or greater hazard intensity on economic consequences (Hypotheses 2c and 3c). These conclusions—good evidence for moderation effects, but evidence of beneficial direct effects of EbA only in few specific cases—are not as clear-cut as the favourable assessments of the effectiveness of EbA in the adaptation literature (e.g., Doswald et al. 2014). Rather, they are in tune with the mixed evaluation of the effects of green and adaptation lending on lender financial performance offered by Dorfleitner et al. (2017), Ayayi and Wijesiri (2022) and Zhou et al. (2022). We attribute our nuanced findings to a mix of several factors, including: first, our survey variables are only imperfect measures of the degree of adaptation, as we discuss at the end of this section. Second, reports of EbA measures may contain additional information on the presence of climatic threats beyond what is explained by the measure of climatic hazards employed. Third, in our pre-intervention setting, measures have been autonomously implemented with potentially low levels of intensity and quality.

The authors are aware of recently completed and ongoing projects combining inclusive finance and ecosystem-based adaptation for which no evaluation is available at this point. For instance, *Microfinance for Ecosystem-based Adaptation* (MEbA) aimed to systematically finance ecosystem-based adaptation in Latin America and SSA and was implemented from 2012 until 2020 in 11 countries. Preliminary and unpublished observational evidence reviewed by the authors suggests that after an intervention combining training, technology and technical assistance to smallholder farmers and MFIs, PAR30 of the portfolio dedicated to financing ecosystem-based adaptation is lower than in the rest of the agricultural portfolio. This suggests that ecosystem-based adaptation has the potential to reduce portfolio at risk at MFIs when combined with complementary services in a targeted intervention.

Regarding the drivers of EbA implementation and financing (Hypotheses 4a and 4b), we find clear evidence of an association between the occurrence of climatic hazards and the autonomous use of EbA measures, as expected from the reviewed research on adaptation and organisational change. The number of different reported hazards also significantly correlates with the number of different EbA measures financed; however, this does not hold when considering the portfolio share invested in financing EbA as a dependent variable. Thus, there is some evidence in favour of Hypothesis 4b, but it does not extend to the portfolio share. Potential explanations for this include MFI-internal and external barriers to adaptation in our pre-intervention setting such as the lack of dedicated financing products (e.g., Helwig et al. 2020) as well as the cost-effectiveness and low capital intensity of many ecosystem-based adaptation measures (Jones et al. 2012; Munang et al. 2013), which may render credit provision less relevant to EbA. Furthermore, field officers may under-report their financing of adaptation actions as they are unaware of the exact use of proceeds.

Complementing the considerations above, we acknowledge several general limitations of our analysis. First, climate change also affects urban communities and non-agricultural activities. Our survey and analysis, however, is focused on the implementation and financing of adaptive actions primarily in the agricultural domain, given the particular sensitivity of agriculture to climatic hazards. Hence, our results do not reflect and do not necessarily generalise to urban and non-farming settings.

Second, the count and score variables constructed from the binary survey responses are only imperfect measures of the underlying phenomena. They may not appropriately reflect the frequency and intensity with which climate change effects occur and with which adaptation measures are implemented and financed. This is mitigated to a certain extent by the use of Likert scale responses for the climate change effects. For adaptation measures, only binary responses are available and the resulting number of different measures and the computed score may not be an appropriate reflection of the extent to which the various measures have been implemented or financed in a certain portfolio. In addition, there may be timing inconsistencies between different variables, as the survey asked for hazards, impacts and consequences observed *in the last three years*, while adaptation measures, *PAR30*, and *EbA_share* are reported as responses at the time of the survey.

Lastly, the analysis of a one-off survey using cross-sectional regressions generally does not permit causal inference. Hence, the evidence we present is of correlational nature and should be interpreted with caution. We rely on the reports of MFI field officers. The information available to each respondent may vary and their reports may not be accurate if the respondent lacks experience, knowledge of their area of operation or their clients, or appropriate records. To mitigate this concern, we present results for the subsample of more experienced respondents (at least three years of *Tenure*) in Section 4.3, which support our findings.

6 | Conclusion

Climate change confronts the microfinance ecosystem with new challenges. Microfinance providers need to adapt their strategy in order to meet the evolving expectations of diverse stakeholders. Using unique data from a survey of MFI field officers across

13 countries in Latin America and the Caribbean as well as sub-Saharan Africa, we provide evidence for the climate vulnerability of MFIs' borrowers. We also demonstrate an association between the intensity of climatic hazards and *PAR30* in microcredit portfolios. These results highlight the need for stakeholder cooperation between MFIs and their microborrowers to develop and implement effective strategies to address climate change. The effective adaptation of microborrowers is not only directly relevant to poverty reduction and related social goals, it is also a financial imperative for MFIs to address the credit risks climate change poses to their portfolios. The collaborative management of climate change adaptation in the MFI—microborrower relationship will be crucial to the continued organisational success of an MFI. A failure to facilitate climate change adaptation in their lending portfolios may cause the MFI to fall short of the evolving expectations of its clients and other stakeholders such as capital providers, regulators, and local communities, with respect to the positive social impact and financial sustainability of microcredit. Thus, the risks emerging from climatic conditions deserve the attention of scholars and practitioners alike. MFIs and their regulators should carefully monitor issues ranging from short-term liquidity risks after extreme weather events to the long-term deterioration of credit quality.

Ecosystem-based adaptation (EbA), as an approach deemed particularly suitable for vulnerable communities and already being widely adopted by smallholder farmers, could be an important strategic tool for MFIs to address climate change. Against this backdrop, our research assesses the baseline and potential of EbA use and financing and demonstrates that EbA measures are a moderating factor dampening the association between increased climatic hazards and greater economic problems for microborrowers. Nonetheless, our findings also suggest that there is much scope to increase the effectiveness of adaptation measures and to support the widespread implementation of EbA measures through increased financing by MFIs. Initiatives in these areas could be a worthwhile endeavour for MFIs to overcome vulnerability to climate change. The documented existing level of autonomous adaptation suggests a fertile ground for such initiatives. However, in the light of the social mission of inclusive finance and past experiences, the benefits of facilitating adaptation through microcredit must be weighed against the risks of over-indebtedness. Further research is needed also on the determinants of effectiveness of adaptation measures. Anecdotal evidence suggests that a low level of planning or a lack of complementary services may have contributed to our rather mixed findings on the effectiveness of ecosystem-based adaptation measures.

Endnotes

[1] The exact nature of these stakeholders may vary with the organisational form of the MFI; it may have shareholders, cooperative members and donors as contributors of equity and depositors as debt providers. An MFI constituted as a bank may also face banking regulators as stakeholders.

[2] The following responses were removed: (a) Responses missing answers to all key survey items (portfolio size, PAR30, agricultural share, all hazard/impact/consequence and EbA reports); (b) responses with repeated invalid entries in free text fields (e.g., 'xxx' or '111'): (c) duplicate responses; (d) responses with a reported *Tenure* below 0.05 years; (e) responses selecting more than 40 of 48 EbA measures as used by clients or financed.

[3] As the Likert scale was not included in all questionnaires, the number of observations is about one third lower compared to the respective count variable, as presented in Table 1.

[4] For Poisson regressions, the coefficient estimate β gives the estimated difference in the logs of expected counts of the explained variable for a one-unit change of the explanatory variable. Absent an interaction term, the estimated percentage change of the explained variable for such one-unit change is hence given by $exp(\beta) - 1$.

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Conflicts of Interest

The authors declare no conflicts of interest.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Appendix A

Additional Information on Variables

A.1 | Description of Variables

TABLE A1 | Description of variables.

Variables of interest	
#Hazards	Number of climate hazards reported by the respective respondent as having been identified in their area of operation in the last three years, from a list of seven hazards provided. *(S)*
#Impacts	Number of impacts for clients from climate threats in the last three years reported by the respective respondent, from a list of 14 impacts provided. *(S)*
#Consequences	Number of economic consequences for clients reported by the respective respondent, from a list of four different consequences provided. *(S)*
Hazard_intensity	Intensity score computed as the sum over the Likert scale responses (low = 0, medium = 0.5, high = 1) to the same list of seven hazards used for *#Hazards*. *(S)*
Impact_intensity	Intensity score computed as the sum over the Likert scale responses (low = 0, medium = 0.5, high = 1) to the same list of 14 impacts used for *#Impacts*. *(S)*
Consequence_ intensity	Intensity score computed as the sum over the Likert scale responses (low = 0, medium = 0.5, high = 1) to the same list of four consequences used for *#Consequences*. *(S)*
#EbA_used	Number of EbA measures reported by the respondent as currently being used by clients, from a list of 48 different measures provided. *(S)*
#EbA_financed	Number of EbA measures to which the respondent has granted credit, from the same list of 48 different measures used in *#EbA_used*. *(S)*
EbA_used_score	Score computed from the EbA measures reported as being currently used by clients with reference to the *extent of impact reduction* score assigned to EbA measures in *Microfinance for ecosystem-based adaption: options, costs, and benefits* (United Nations Environment Programm (UNEP) and Frankfurt School-UNEP Collaborating Centre for Climate and Sustainable Energy Finance 2014). Based on impact reduction scores from zero to three for 34 of the 48 different measures surveyed, the final *EbA_used_score* can range from zero to 80. *(S, UNEPFS)*
EbA_fin_score	Score computed from the EbA measures reported as being financed, following the same methodology as *EbA_used_score*, resulting in a possible zero to 80 range. *(S, UNEPFS)*
PAR30	Ratio of the reported portfolio at risk for more than 30 days in USD to the reported current portfolio size in USD. *(S)*
EbA_share	Proportion of the respondent's portfolio used to finance EbA measures, computed as the ratio of the reported current gross portfolio in EbA solutions in USD to the current portfolio size in USD. *(S)*
Control variables	
Agri_share	Proportion of the respondent's portfolio consisting of agricultural lending, obtained by dividing the reported outstanding agricultural portfolio size in USD by the current portfolio size in USD. *(S)*
Tenure	Respondent's years of employment with the MFI. *(S)*
ALSGNI	Size of the average loan in the respondent's portfolio relative to the relevant country's gross national income (GNI) per capita. Average loan size is calculated by dividing the reported current portfolio size in USD by the reported total number of current credits. *(S, World Bank)*
#Credits (ln)	Natural logarithm of the reported number of current credits in the respondent's portfolio. *(S)*
Growth	Real GDP growth rate observed in the respondent's country, in the response year. *(IMF)*
C19_measures	Stringency index from the *Oxford COVID-19 Government Response Tracker*, capturing the strictness of 'lockdown' policies. Index value matched to the date and country of each survey response. *(University of Oxford)*
Assets (ln)	Natural logarithm of each MFI's total assets in USD. *(A, SEPS, RW)*
DTE	Debt to equity ratio of each MFI, computed as total liabilities over total equity. *(A, SEPS, RW)*
OSS	Indicator for operational self-sufficiency of each MFI, obtained by dividing financial revenue by the sum of financial expense, operating expense and impairment losses on loans. *(A, SEPS, RW)*

(Continues)

TABLE A1 | (Continued)

Control variables	
MFI	Categorical variable referencing the respondent's MFI. For project A, responses are not grouped by MFI, so one MFI per country is assumed. The reference MFI is a Colombian NGO from project D. *(S)*
Country	Categorical variable describing the respondent's country. The reference country is Colombia. *(S)*
MFI type	Categorical variable describing each MFI's charter type. Categories are *Bank*, *Cooperative*, *Non-bank financial institutions* (NBFI), *Non-governmental organisation* (NGO) and *Others*. The reference category is NGO. *(A, RW)*
Plant, *Harvest*	Two indicator variables coded based on the date of the survey submission. *Plant* indicates if the survey is submitted during the planting time of a main crop, *Harvest* indicates submission during the harvesting season of a main crop. Both variables are not mutually exclusive as planting and harvesting may overlap for different crops. *(S, USDA)*

Note: This table describes each variable used in the subsequent regression analyses. The corresponding data source is indicated in brackets; *(S)* denotes the survey data set, *(A)* denotes Atlasdata.org, *(SEPS)* denotes the Ecuadorian *Superintendencia de Economia Popular y Solidaria*, *(RW)* denotes MFI reports and webpages, *(UNEPFS)* denotes the UNEP and Frankfurt School-UNEP Collaborating Centre for Climate & Sustainable Energy Finance and *(USDA)* denotes the US Department of Agriculture's Foreign Agricultural Service.

A.2 | Correlation Table

TABLE A2 | Correlations, all available observations.

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1)	*#Hazards*	1.00																				
(2)	*#Impacts*	0.62	1.00																			
(3)	*#Consequences*	0.54	0.66	1.00																		
(4)	*Hazards_ intensity*	0.69	0.45	0.33	1.00																	
(5)	*Impact_intensity*	0.38	0.75	0.47	0.53	1.00																
(6)	*Consequence_ intensity*	0.26	0.47	0.62	0.38	0.64	1.00															
(7)	*#EbA_used*	0.31	0.40	0.36	0.16	0.24	0.23	1.00														
(8)	*#EbA Fin.*	0.23	0.29	0.24	0.11	0.12	0.13	0.77	1.00													
(9)	*EbA_used_score*	0.32	0.40	0.36	0.16	0.24	0.22	0.97	0.74	1.00												
(10)	*EbA_fin_score*	0.25	0.29	0.23	0.11	0.12	0.11	0.71	0.95	0.74	1.00											
(11)	*Agri_share*	0.10	0.20	0.07	0.13	0.15	0.05	0.16	0.18	0.16	0.17	1.00										
(12)	*Tenure (ln)*	0.03	0.07	0.14	−0.05	0.10	0.15	0.10	0.04	0.08	0.01	−0.10	1.00									
(13)	*ALSGNI*	−0.03	−0.05	0.06	−0.02	0.00	0.12	−0.05	−0.09	−0.06	−0.11	−0.03	0.10	1.00								
(14)	*#Credits (ln)*	0.01	−0.02	0.04	−0.02	0.06	0.08	−0.01	0.05	0.01	0.07	−0.14	0.47	−0.22	1.00							
(15)	*Growth*	−0.08	0.07	−0.03	0.14	0.25	0.06	−0.02	−0.01	−0.04	0.00	−0.02	−0.04	−0.26	0.13	1.00						
(16)	*C19_measures*	0.19	0.06	0.13	−0.08	−0.13	−0.07	0.10	0.12	0.13	0.14	0.17	−0.04	0.17	−0.11	−0.69	1.00					
(17)	*Assets (ln)*	0.19	0.02	0.15	−0.12	−0.13	−0.01	−0.01	0.04	0.03	0.05	−0.05	0.07	0.18	0.12	−0.59	0.41	1.00				
(18)	*DTE*	−0.11	−0.05	−0.06	−0.03	0.13	0.12	−0.11	−0.14	−0.10	−0.13	−0.11	0.12	0.41	0.07	−0.29	0.21	0.22	1.00			
(19)	*OSS*	0.06	−0.04	0.02	0.07	0.01	0.04	0.06	0.13	0.08	0.12	0.04	−0.07	−0.04	−0.08	−0.03	0.02	0.22	−0.30	1.00		
(20)	*PAR30*	0.11	0.11	0.09	0.09	0.07	0.05	0.04	0.05	0.05	0.07	0.06	0.07	−0.15	0.06	0.09	−0.06	0.05	−0.12	−0.03	1.00	
(21)	*EbA_share*	0.08	0.12	0.06	0.07	0.09	−0.02	0.18	0.26	0.18	0.27	0.35	0.01	−0.15	0.06	0.15	−0.06	−0.03	−0.14	−0.03	0.04	1.00

Note: This table reports pairwise Pearson correlation coefficients for all variables used in the main regressions, using all observations available for each pair. For *PAR30* and *EbA_share*, observations are only available for projects B and D.

Appendix B

Additional Survey Results

TABLE B1 | Frequency table of hazards, impacts and consequences, by region.

	LAC		SSA		Total	
	(1)	(2)	(3)	(4)	(5)	(6)
Survey item	*N*	% yes	*N*	% yes	*N*	% yes
Hazards						
Frost	1218	34	94	24	1312	33
Heat extremes	1284	73	101	54	1385	72
Abrupt temp. changes	1261	69	101	49	1362	68
Hail	1217	24	98	30	1315	24
Heavy rain	1262	75	101	47	1363	73
Chg. of rainfall patterns	1325	82	104	84	1429	82
Strong winds	1249	57	101	38	1350	56
Any of the above	1346	96	105	93	1451	96
Impacts						
Crop damage	1255	70	102	66	1357	70
Crop losses	1290	71	102	69	1392	71
Need for more inputs	1246	66	103	51	1349	65
Productivity losses	1286	76	102	82	1388	76
Reduced food safety	1089	46	98	51	1187	47
Avenues	1182	16	95	18	1277	16
Drought	1298	69	102	32	1400	66
Erosion	1210	33	100	29	1310	32
Fires	1216	26	101	20	1317	25
Floods	1238	40	100	40	1338	40
Landslides	1230	27	100	15	1330	26
Increase in pests	1258	59	98	38	1356	58
Phenological changes	1215	32	93	20	1308	31
Reduced water availability	1245	59	100	56	1345	59
Any of the above	1344	94	105	93	1449	94
Economic consequences						
Decr. income per unit	1258	76	104	44	1362	74
Incr. cash flow variability	1269	70	90	70	1359	70
Incr. cost of crop production	1272	79	103	58	1375	78
Loss of income sources	1260	75	78	64	1338	74
Any of the above	1318	94	105	90	1423	93

Note: This table reports, for all survey items in the three categories climate hazards in the area, impacts for clients and economic consequences for clients, the number of valid responses (*N*) and the share of responses indicating that the survey item has been observed by the respondent (*% yes*). *Any of the above* is computed using all survey responses including at least one valid answer to a survey item in the relevant category. Here, *N* refers to the all respondents with at least one valid answer to a relevant survey item. Columns 1–2 report the results for Latin and Central America (LAC), Columns 3–4 for Sub-Saharan Africa (SSA) and Columns 5–6 present the aggregated results across both regions.

TABLE B2 | Most-used EbA measures and corresponding financing, by region.

	(1)	(2)
EbA measure	% reporting use	Of which financed %
LAC		
1. Organic agriculture	59	55
2. Organic inputs	51	49
3. Crop rotation	49	53
4. Greenhouses	49	68
5. Drip irrigation	45	62
N	1281	1220
SSA		
1. Crop diversification	66	43
2. Crop rotation	60	48
3. Organic agriculture	50	44
4. Organic inputs	43	49
5. Solar home system	40	8
N	96	96
Total		
1. Organic agriculture	58	54
2. Organic inputs	50	49
3. Crop rotation	50	53
4. Greenhouses	46	67
5. Drip irrigation	43	62
N	1377	1316

Note: This table reports the adaptation measures with the highest share of responses indicating use by clients (Column 1). In addition, Column 2 displays the share of respondents also indicating having granted credit towards this particular measure, conditional on reporting its use.

TABLE B3 | Most-financed EbA measures, by region.

EbA measure	(1) % reporting financing	(2) % financed given use
LAC		
1. Greenhouses	34	68
2. Organic agriculture	33	55
3. Drip irrigation	29	62
4. Crop rotation	27	53
5. Organic inputs	25	49
N	1220	1220
SSA		
1. Crop rotation	29	48
2. Crop diversification	28	43
3. Organic agriculture	22	44
4. Organic inputs	21	49
5. Pisciculture	20	56
N	96	96
Total		
1. Organic agriculture	32	54
2. Greenhouses	32	67
3. Drip irrigation	27	62
4. Crop rotation	27	53
5. Organic inputs	25	49
N	1316	1316

Note: This table reports the adaptation measures with the highest share of respondents reporting having granted credit towards (Column 1). Column 2 additionally shows the share of respondents indicating having granted credit towards this particular measure, conditional on reporting its use (as in Column 2 of Table A4).

TABLE B4 | Most-financed EbA measures given reported use, by region.

EbA measure	(1) % financed	(2) *N*
LAC		
1. Pisciculture	74	335
2. Greenhouses	68	613
3. Apiculture	62	375
4. Drip irrigation	62	561
5. Improved pasture	56	360
SSA		
1. Enhanced oven	67	6
2. Conservation agriculture	65	23
3. Intelligent storage	60	10
4. Silvopastoral system	60	5
5. Pisciculture	56	34
Total		
1. Pisciculture	72	369
2. Greenhouses	67	620
3. Drip irrigation	62	581
4. Apiculture	62	385
5. Improved pasture	56	360

Note: This table reports the adaptation measures with the highest share of respondents reporting having granted credit towards, conditional on reporting the use of this particular measure by clients. This corresponds to Column 2 of Tables A4 and A5.