Resilience of agricultural microfinance institutions to rainfall shocks

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Abstract

This paper adds nuance to our understanding of how systemic events are transmitted to the Microfinance Institutions (MFI). Using a unique longitudinal dataset of agricultural MFIs in Peru, Ecuador, and Mexico, the paper first shows that rainfall shocks have a statistically significant effect on indicators of credit risk and profitability. Next, it tests if such effects are influenced by the cost of funds. The analysis is guided by the optimality conditions of a theoretical model that suggests that MFIs with relatively higher cost of access to extra funds are able to reduce their nonrepayment rate when facing systemic events as immediate response strategy, being able to show sustained financial resilience capabilities. The econometric estimates are consistent with the theoretical implication, showing that the extent of the effect of precipitation shocks on the profitability and portfolio at risk is significantly influenced by the cost of funds.

Keywords: Financial resilience, rainfall shocks, portfolio quality, profitability, funding costs.

1. Introduction

The renewed interest of researchers and practitioners in the creation of sustainable microfinance institutions is to a large extent motivated by the ongoing market transition of the microfinance industry, from non-for profit driven organizations towards commercial microbanks (Conning & Morduch, 2011; Cull, Demirgüç-Kunt, & Morduch, 2009; Baquero, Hamadi, & Heinen, 2012). Intrinsic to the evolution of microfinance markets researchers have pointed out an increasing competition for funds (Biekpe & Kiweu, 2009; Bhanot & Bapat, 2014; Le Saout & Daher, 2016), which by driving the costs of funds up may influence the capacity of Microfinance Institutions (MFIs) to become sustainable[1]. This paper presents an analysis of how the loan portfolio quality and profitability of agricultural MFIs, as determinants of sustainability, respond to rainfall shocks, considering the increasing market competition for funds. We concentrate only on agricultural MFIs because, due to a comparatively stronger dependence on governments and donors funding, and higher vulnerability to weather conditions, their capacity to generate sustained revenues appears more exposed to the changing market landscape.

Even though the more market oriented features of the microfinance industry are relatively recent, the concerns about sustainability of microfinance programs arose with the inception of the industry (Adams & Von Pischke, 1992; Adams & Vogel, 2014). Researchers pointed out that the advent of microfinance resembled earlier efforts to assist small farmers with credit and that the persistence of factors that contributed to the failure of those credit schemes such as large transactions costs of lending and reliance on funding from donors and government subsidies would also jeopardize the

[1] Financial sustainability broadly refers to the capacity of MFIs to cover operational and financial costs by its revenue. The MicroBankig Bulletin (March, 2005) classifies sustainability of MFIs based on their level of financial self-sufficiency measured as the following ratio: (Adjusted) financial revenue/ (Adjusted) financial expense + net loan loss provision expense + operating expense

prospects of microfinance. However, unlike conventional credit programs, the microfinance agenda has enjoyed flexibility to set interest rates, has triggered innovative lending mechanisms, and has introduced a more diversified array of financial services, which has permitted a continuous expansion of the industry. Nonetheless, in light of an apparent trade-off between outreach and profitability (Von Pischke, 1996; Mosley, 1998; Conning, 1999; Cull, Demirgüç-Kunt, & Morduch, 2007; Hermes, Lensink, & Meesters, 2011), and more recently, of an increasing industry competition (Navajas, Conning, & Gonzalez-Vega, 2003; McIntosh & Wydick, 2005; Gosh & Van Tassel, 2011; Baquero, Hamadi, & Heinen, 2012; Cull, Demirgüç-Kunt, & Morduch, 2014), sustainability of MFIs has remained a subject of close scrutiny.

We study only MFIs that lend to agricultural producers. Our interest in the agriculture sector obeys three interconnected empirical observations. First, agriculture remains a large source of income for development countries. Agriculture income represents more than 20 percent of the gross domestic product (GDP) for over half of the 48 nations classified as the least developed by the United Nations, and for 10 out of them it accounts for over 40 percent (IFAD, 2011). Second, there is abundant evidence on the positive role of access to financial services on agricultural productivity (Hazell, 1992; Wenner, 2005; Trivelli & Vereno, 2007; Mahul & Stutley, 2010). The influence of removing financial constraints on higher-productivity choices is ubiquitous in the development literature (Yaron, 1994; Dercon & Christiaensen, 2011; Giné and Yang, 2009; Dupas & Robinson, 2013), yet the Byerlee, et al., (2008) reported that from 400 to 500 million-smallholder farmers in low and middle-income countries face limited access to financial services. The World Bank (2010) points out that agricultural financial services in Latin America remain stagnated thus limiting rural population to financial services access. And third, agricultural income is highly vulnerable to the occurrence of systemic shocks. The Food Agriculture Organization of the United Nations, FAO

(2015) denotes that droughts, storms, and floods are the three major types of hazards to the agriculture sector. The cited study shows that these types of natural disasters increase rural unemployment and have a negative effect in the income of farmers. The occurrence of these regional systemic shocks has been a subject of major concern to the financial development literature because, due to the strong correlation of agricultural incomes, a systemic event may severely damage the capacity of farmers to honor financial obligations further threatening their inclusion into formal financial markets. Natural shocks then can degrade the quality of the loan portfolios of MFIs, in the aggregate, discouraging the emergence and development of formal lending markets.

Governments, donors, and practitioners have not overlooked the uniqueness of the agricultural industry. Unsurprisingly, such interest has often been reflected by comparatively more favorable costs of funding to agricultural MFIs (Miller, Ritcher, McNellis & Mhlanga, 2010; Cheng & Ahmed, 2014).

Researchers have also placed special attention to mechanisms that help to mitigate the exposure of agricultural producers (and indirectly of MFIs) to the vagaries of climate. Departing from conventional policies of indemnity-based insurance products, which have failed to penetrate in rural agricultural markets due to problems of information asymmetry, high transaction costs, limited contract enforceability, and the covariate risk itself (Hazell, 1992); more recently, researchers have devised index-based weather insurance schemes (Turvey, 2001; Skees et al., 2006; Odening & Zhiwei, 2014).

Index insurance bases its indemnities upon the observable value of a specified index, which ideally is a random observable and measurable variable, highly correlated with the losses of the insured, and uninfluenced by the actions taken by the insured farmer. Since there are no loss adjustments at the farm-level but indemnities are determined by the realization of the index, the asymmetric information problems and high loss adjustment expenses are circumvented. Despite these advantages, multiple index insurance initiatives (often heavily subsidized) have not enjoyed great success either (Miranda & Farrin, 2012; Odening & Zhiwei, 2014). Miranda and González-Vega (2011) have indeed suggested the use of index-insurance as a reinsurance instrument to be used by the microfinance institution rather than by individual producers.

Given the importance of access to finance in agriculture and both the market and natural challenges to create sustainable lending institutions, finding effective hedging strategies that permit agricultural MFIs to achieve sustainability is of utmost relevance. To better understand and address this issue, however, we consider necessary to build a solid basis on the magnitude and channels through which weather shocks can affect the financial institutions.

2. Research questions and literature review

This paper seeks to add nuance to our understanding of how rainfall shocks are transmitted to the MFI by answering two questions:

1. What is the effect of rainfall shocks on the quality and profitability of agricultural loan portfolios?
2. Do financing costs influence the resilience of the quality and profitability of agricultural loan portfolios to those shocks?

The answer to the first question is important because the published evidence on the actual effect of weather shocks on the financial performance of the agricultural MFIs is still scant. Related studies are those of Collier, Katchova, and Skees (2011), and Pelka, Musshoff, and Weber (2015). Using time series data, Collier *et al*. shows that the occurrence of the El Niño event significantly increased the number of restructured loans for one MFI in Peru. Pelka *et al.* use farm-level data to show that excessive precipitation in harvesting periods reduced the on-time repayment of loans granted to small farmers for a MFI in Madagascar. Our econometric approach to answer this query differs in key dimensions.

We construct a unique longitudinal dataset at the MFI level employing financial information from a set of institutions in Ecuador, Mexico, and Peru, rainfall data from the nearest weather stations for each one of the agricultural – loan users settlements, and domestic macroeconomic indicators of the three countries. The longitudinal dataset is advantageous because, apart from allowing us to track crucial financial indicators over time, it allows us to account for unobserved heterogeneity. An additional advantage of a longitudinal data set over cross-sectional or time series data is that it offers a larger number of observations, which reduces the collinearity among explanatory variables, improves the efficiency of the coefficient estimates, and increases the degrees of freedom, providing us with enough information to address potential endogeneity of the variables within a dynamic framework. We then estimate the effect of rainfall shocks on profitability and quality of loan portfolio, where profitability is represented by the rate on equity (ROE) and loan portfolio quality takes indicators of delinquency (loan loss ratio, LLR, and write-off ratio, WOR) and of risk (Portfolio at Risk over 30 days, PAR 30, and Portfolio at Risk over 90 days, PAR 90).

The second question aims to determine the influence of the costs of funds on the susceptibility of the MFIs to rainfall changes. To our knowledge, no published evidence documents this relationship. In order to guide the empirical analysis, we develop a theoretical model of financing restrictions and profitability in which the MFI chooses the funding and lending amounts that maximize its expected returns. The first order conditions suggest that MFIs with relatively high cost of access to extra funds are more resilient to systemic events. We verify this econometrically by testing if the effects of rainfall shocks are conditional on the magnitude of financing expenses.

The econometric analysis uses both static and dynamic model specifications. The first set of regressions runs a simple fixed effects models. Next, to address endogeneity between the financial variables of interest, the same model is estimated instrumenting them with lagged variables in a second set of regressions. The estimates from these static models provide initial responses to the research questions, however, the dynamism in MFIs choices described in the theoretical model is left out. Subsequently, a third set of regressions is run within a dynamic panel data framework. This will help us to capture time-dependence of financial performance and the dynamic choices of the MFIs. Here the estimations are carried out applying the Generalized Method of Moments (GMM) suggested by Arellano and Bond (1991), using lagged differences as instruments.

The results indicate that rainfall shocks have statistically significant effects on indicators of risk PAR30. To answer the second research question we verify whether the negatives effects on response variables are mitigated by the cost of funds by looking at the results from the interaction terms. The coefficients indicate that the effect of the shocks on the quality of the loan portfolio PAR30 depend on the cost of funds. The higher the cost of funds, the lower the negative effect to the shock on this response variable.

Similarly, our estimates show that annual returns on equity are statistically sensitive to precipitation shocks. Consistent with the theoretical implications, the variables of shock remain statistically relevant when interacted with FEFL, but with reversed sign. Overall, the empirical evidence validates the premise that higher costs of funds influence the degree of susceptibility of portfolio quality and profitability of MFIs to systemic events. We cannot claim that higher funding costs cause more resilient financial indicators, as the results illustrate a clear relationship between them, but that they serve to ameliorate financial risk indicators as possible immediate response strategy.

Our findings can aid practitioners to develop strategies focused on building sustainable lending institutions as they show the magnitude and channels through which weather shocks influence the financial performance of the MFIs. These results may also help in the design of funding policies that facilitate the development of agricultural regions. The remainder of the paper proceeds as follows. Section III develops the theoretical model. Section IV presents the data. Section V describes the econometric strategy and results and section VI concludes.

3. A Simple Model of Funding and Lending Choices for MFIs

The agricultural MFI of our interest is a risk-neutral lender that seeks to maximize the returns derived from its borrowing and lending activities. Each period it begins with a predetermined stock of capital K, which can be increased if the MFI decided to borrow in the interbank market an amount M, in exchange for a per-period interest payment r_{M}. Next, the micro lender apportions L to current loans. Then the limit to outstanding loans is a function of the total available funds, $max(L) \leq h(K, M)$, where the function h is assumed to satisfy economic and regulatory capital requirements, $0 \leq h'(\cdot) \leq 1$.

The market interest rate on loans is r_L and the lending costs, $c(L)$, are assumed to increase at increasing rates, thus $c' > 0$ and $c'' \leq 0$. The remainder $K + M - L$ is retained as current dividends for the shareholders. The amount of capital available next period follows a stochastic process:

$$K_{t+1} = (1 - \tilde{p}_{t+1})(1 + r_L)L_t - (1 + r_M)M_t$$

where $\tilde{p} \in (0,1)$ is the random non repayment loan rate. We assume that the occurrence of a natural shock such as excessive or lack of rainfall increases the value of p. This assumption is empirically verified in the econometric section, where we determine the effect of rainfall shocks on different measures of the quality of the loan portfolio. This MFI is precluded from investing in the interbank market, so that *M* is strictly non-negative.

The state transition function is:

$$g(L, M, \tilde{p}) = (1 - \tilde{p})(1 + r_L)L - (1 + r_M)M_t \quad (1)$$

and the reward function is:

$$f(K, L, M) = K + M - L - c(L) \quad (2)$$

The MFI maximizes the current and expected future dividends over an infinite time horizon, given its current stock of capital *K*. The dynamic optimization problem is characterized by the Bellman equation:

$$V(K) = \max_{\substack{M \geq 0 \\ h(K,M) \geq L \geq 0}} [K + M - L - c(L)] + \delta E_{\tilde{p}} V(g(L, M, \tilde{p})) \quad (3)$$

where $\delta \epsilon (0,1)$ is the MFI's per-period discount factor.

The solution to the dynamic model will be a set of policies that prescribe the actions the MFI would take in order to maximize the present value of the dividends. Although the nature of the model limits obtaining an analytical solution, the Euler conditions shown as follows help underpinning some essential features:

$$[M]: \quad 1 + \mu h'_M + \delta E_{\tilde{p}} \lambda\big(g(L, M, \tilde{p})\big) g'_M(\cdot) = 0 \quad (4)$$

$$[L]: \quad \delta E_{\tilde{p}} \lambda\big(g(L, M, \tilde{p})\big) g'_L(\cdot) = 1 + c'(l) + \mu \quad (5)$$

where μ measures the present value of the rewards derived from a marginal increase in the amount of funds available for lending. Alternatively, it represents the costs or rewards forgone given the funding restrictions. The marginal value of the state variable, K, to the MFI represented by $\lambda(K)$ is:

$$1 + \delta E_{\tilde{p}}\lambda\big(g(L, M, \tilde{p})\big)g'_K(\cdot) + \mu h'_K(\cdot)$$

Since the state transition depends only on the decision taken by the agent, $g'_K(L, M, \tilde{p}) = 0$, and $\lambda(K) = 1 + \mu h'_K$. Equations (4) and (5) reduce to

$$[M]: \quad \frac{1+\mu h'_M}{1+\mu h'_K} = \delta(1 + r_M) \tag{6}$$

$$[L]: \quad \delta E_{\tilde{p}}(1 - \tilde{p})(1 + r_L) = \frac{1+c'(L)+\mu}{1+\mu h'_K} \tag{7}$$

An interior solution for (6) indicates that the optimal borrowed funds make its marginal benefits equal to its discounted marginal cost. When the solution binds, increasing borrowed funds will increase the present value of all future dividends only when the loans created from an extra unit of borrowed capital exceed the amount of loans that an extra unit of equity capital would produce ($h'_M > h'_K$).

The main implications for this paper come from equation (7). An interior solution implies that the optimal amount of loans the MFI originates make the marginal lending cost equal to the discounted "effective" gross interest rate earned on the loan. A binding solution ($\mu > 0$), directly links the optimal size of the loan portfolio to the constraint associated with the funding costs. In particular, the lender could increase the lifetime profitability by expanding the amount lent as long as $\delta(1 - E[\tilde{p}])(1 + r_L)$ is strictly gretater than $\frac{1+c'(L)+\mu}{1+\mu h'_K}$. It follows then that, *ceteribus paribus*, a high intrinsic financing cost, μ, would induce the microlender to reduce its expected nonrepayment rate

$E(\tilde{p})$. This is equivalent to state that large costs of accessing to extra funds would encourage MFIs to create strategies to ameliorate the effects of the shock on the quality of outstanding loans.

In the following sections, we empirically test the effects of rainfall changes on the quality of loans and profitability, and whether these effects are conditional on the cost of accessing to funds. For the theoretical implications to be consistent with the empirical results, we should find that systemic events undermine the quality of the loan portfolio and profitability of the MFIs and that such effects are less severe for institutions that face higher costs of funds.

4. Data description

The financial information of MFIs comes from the Microfinance Information Exchange Inc. (Mix Market). This analysis focuses on Latin America, a region expected to be greatly affected for changes in climate conditions (Nagy *et al.*, 2006). The Mix market publishes data of 436 MFIs that operate in 24 countries in the region. For consistency with the problem of interest, we select MFIs that generate agricultural loans. Additionally, we consider only the subset of institutions for which most financial indicators are reported over the longest time frame possible. The resulting sample contains yearly data of 47 MFIs located in Ecuador, Mexico, and Peru, from 2011 to 2015[2]. These countries host the largest number of agricultural MFIs in Latin America reporting to the MIX market and their combined Gross Loan Portfolio (GLP) represents 35 percent of the total GLP of the 436 MFIs from 2011 to 2015.

The information of precipitation was obtained from meteorological and hydrological agencies of every country. For the Peruvian MFIs the information was obtained from *Servicio Nacional de Meteorología e Hidrología del Perú* (SENAMHI). For Ecuadorian institutions, from the *Instituto*

[2] The list of all MFIs selected can be found in Table A5, Appendix section.

Nacional de Metereología e Hidrología (INAMHI), and for the Mexican institutions from Instituto Nacional de Investigaciones Forestales, Agrícolas y Pecuarias (INIFAP). The sources for macroeconomic and agricultural information are specialized domestic agencies.

Economic data represents the annual gross domestic (GDP) product grouped by economic activities, by departments or cantons and referenced to agriculture, livestock and fishery. The agricultural information refers the planting and harvest area of the basic crops. In the case of Peru, economic and agricultural information is provided by the *Instituto Nacional de Estadística e Informática* (INEI) and the Agricultural Statistic Annual Reports, generated by Agricultural Agency (MINAGRI) at its Statistical Unit, at the *Sistema Integrado de Estadísticas Agrarias* (SIEA); respectively. In the case of Ecuador, the agricultural GDP data was obtained from by the National Unit of Macroeconomic Synthesis (*Dirección Nacional De Síntesis Macroeconómica*), which is available at the portal of the Central Bank of Ecuador. The planting and harvest area data is prepared by the *Instituto Nacional de Estadística y Censos* (INEC), which is the result of the Annual Agricultural Survey of Agricultural Production (ESPAC). In the case of Mexico, the agricultural GDP information was taken from the *Instituto Nacional de Estadística y Geografía* (INEGI). The planting and harvest data was consulted from *Servicio de Informacion Agroalimentaria y Pesquera* (SIAP), at its agricultural section. We converted all the economic information into real units and million dollars according average exchange rates of each year and countries.

Rainfall data was obtained from weather stations previously referred, based on a three-stage process. First, we identified the zones where the MFIs offered services whether by consulting directly workers at the institution or by referring to their web page services. Next, we looked for the nearest agricultural production settlements that operated in these zones[3]. Finally, we identified the weather stations nearest to these agricultural zones.

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4.1. Description of dependent variables

The dependent variables of loan quality include two measures of portfolio risk (PAR30 and PAR90) and two measures of portfolio delinquency (LLR and WOR), while profitability is represented by the return on equity (ROE). Portfolio at risk (PAR) broadly refers to the outstanding amount of loans with at least one delinquent installment over 30 days, PAR30, or over 90 days, PAR90. Portfolio at risk is calculated as the ratio of outstanding balance of all loans with arrears over the period under consideration to the total outstanding gross portfolio (Von Stauffenberg *et al*., 2003).

Write offs are loans removed from the loan portfolio balance because they were deemed uncollectable. The write-off ratio (WOR) is the fraction of total write-offs to the average gross loan portfolio. Loan loss rate (LLR), as a measure of unrecovered loans, is calculated by dividing the total written-offs minus the loans recovered during period by the average gross loan portfolio. Finally, the return on equity (ROE) is the proportion of net operating income minus taxes to the

[3] The criteria was to review the basic economic activities of the regions as well as their crop production amounts. i.e., agricultural gross domestic product and the planting - harvest crop amounts.

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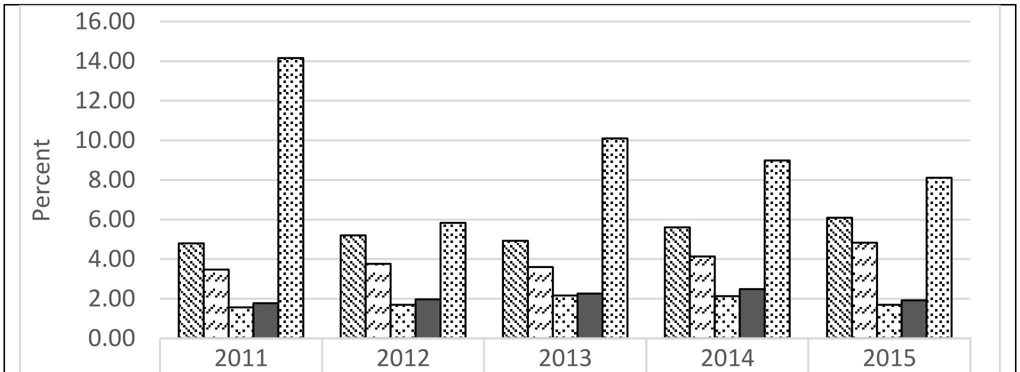
average equity. It represents a close measure of financial sustainability and for MFIs plays a crucial role in the search of potential investors (CGAP, 2003).

Figure 1. Average values of PAR30, PAR90, LLR, WOR and ROE



	2011	2012	2013	2014	2015
PAR30	4.794	5.195	4.928	5.599	6.094
PAR90	3.470	3.770	3.598	4.135	4.829
LLR	1.571	1.690	2.159	2.135	1.694
WOR	1.775	1.968	2.264	2.484	1.916
ROE	14.162	5.829	10.107	8.981	8.112

Source: Authors' calculations from data from the MIX market and the World Bank.

Average values of all dependent variables are displayed in Figure 1. As it can be seen, PAR30 and PAR90 remained below 6.1 and 4.8 percent in every year respectively. These values indicate that borrowers tend to pay back loan installments by the due date more often over 90 days than over 30. It is worth nothing that these values of PAR30 and PAR90 reflect financially sound loan portfolios[5] and, except for 2015 where both measures appear slightly higher, they suggest the quality of portfolios are also fairly stable. Occasionally, institutions implement policies to improve indicators of risk at the expense of higher delinquency measures. This does not appear to be the case for our sample, as the indicators of default, LLR and WOR, fluctuate narrowly around 1.5

[5] In the industry, a PAR30 exceeding 10% is considered cause for concern (Von Stauffenberg *et al.*, 2003)

and 2.5 percent respectively, suggesting genuinely sound loan portfolios. The values of ROE indicate a relatively high profitability in 2011 (14.16 percent) that declined abruptly in the following year (5.82 percent) with a moderate recuperation in 2013 (10.1 percent), and followed by decreases in their values. Droughts and floods in productive areas (FAO, 2013) of Peru and Ecuador caused significant loses of basic products like corn, potatoes, and coffee during those years (2012 to 2014) that may explain the declines in profitability. The econometric analysis will help us to reveal if a statistically significant relationship exists.

4.2. Description of the main independent variables

Values of monthly precipitation, obtained from local weather stations, are used to compute four variables of seasonal precipitation. Next, similar to Maystadt and Ecker (2014) and Pelka et al., (2014) we employed the sum of monthly-seasonal deviations from historic mean values[6] and historic standard deviations of rainfall for each of the two agricultural seasons to represent the shocks. In general, the precipitation shock corresponds to the rainfall sum within a certain accumulation period[7] n comprising the two different seasons in year y; the shock values follow:

$$Shock_{i,m,s,y} = \frac{1}{n}\sum_{s=1}^{2}\sum_{m=1}^{n}\frac{P_{i,m,s,y}-\mu_{i,m,s}}{\sigma_{i,m,s}} \tag{8}$$

Where $P_{i,m,s,y}$ refers to the seasonal total precipitation rainfall tracked at the weather station i during the months comprising the two possible seasons along the year (s, y) time frame. The long-term monthly-seasonal mean precipitation is $\mu_{i,m,s}$ and the long term monthly-seasonal standard deviation is $\sigma_{i,m,s}$. The time frame for historic precipitation and standard deviation is from 1999 to 2012 in each of the selected locations i. To capture the cumulative nature of precipitation

[6] Historic mean values refer the average precipitation from 1999 to 2012 in each of the selected locations. Source: The World Bank Climate Change Knowledge Portal, 2017.
[7] Appendix section includes a description of months comprising the seasons for each country.

extremes, we average precipitation over the number of successive months or accumulation period n comprising the season s according each region, where $\bar{n} = 6$ as the average of successive months for all countries.

The period for the analysis of precipitation is from 2011 to 2015. For example, Table 1 shows the descriptive statistics for the two seasonal precipitation variables in millimeters over the time considered. By comparing average values across seasons, one can see that heavy rainfall occurs in summer, and drops in the following winter season. The mean values for shock seasons summer and winter support as well this tendency (2.99 and -0.86) Although mean values are generally stable over the years, *min* and *max* values within the seasons could portray a story of uncertainty about rainfall for farmers. For example, in the winter season the average rainfall precipitation is around 164 mm (179mm in 2011, 136.3 mm in 2012, 151.7 mmm in 2013, 183.7 mm in 2014 and 169.5 in 2015), however in the same season some regions experienced droughts (0 mm in 2012, 2013, 2014 and 2015) and excessive rainfall (917.2 mm in 2013). These extreme values are expected to influence the business agricultural finance institutions.

Table 1. Descriptive statistics of seasonal precipitation (millimeters), from 2011 to 2015

Year	Crop season	Obs	Mean	StDev	Minimum	Maximum
2011	Pptation Summer&Autum	47	842	662.2	3	2411.1
	Ppation Winter&Spring	47	179	176.7	0.2	815
2012	Pptation Summer&Autum	47	928	801	6	3918
	Ppation Winter&Spring	47	136.3	158.9	0	605.9
2013	Pptation Summer&Autum	47	782.1	614.6	1.6	2680.6
	Ppation Winter&Spring	47	151.7	185	0	917.2
2014	Pptation Summer&Autum	47	901	791	2	3219
	Ppation Winter&Spring	47	183.7	197.9	0	894
2015	Pptation Summer&Autum	47	718.7	684.8	3.8	3789.1
	Ppation Winter&Spring	47	169.5	177	0	768.5
HistoricAverage Precipitation (SummerAutum)		235	915.4	469.5	109.3	1937.7
Historic Average Precipitation(Winter&Spring)		235	265.1	202.6	26.4	947.6
Shock Summer		235	2.99	5.567	-2.62	19.74

Shock Winter	235	-0.86	1.642	-5.637	10.162

Source: Authors' calculation using data from Weather stations and The World Bank Climate Knowledge Portal.

To address the second research question we incorporate financial expenses on funding liabilities (FEFL) as a proxy for cost of funds. FEFL refers to all costs incurred in raising funds from third parties, including deposits, borrowings, subordinated debt and other financial obligations, in addition to fees expenses from non-financial services (MIX, 2017). FEFL includes commercial and concessional borrowings. Commercial borrowings are the Funds received by an MFI through a loan agreement or other contractual arrangement that carry a market rate of interest. (Von Stauffenberg, 2003)[8]. Other control variables include measures of financial structure, economic activity, and total planting area[9]. Table A3 in Appendix presents descriptive statistics of all variables used in the econometric exercises.

5. Estimation Strategy and Results

A generic representation of the model of interest is expressed as a MFI fixed effects model as follows:

$$y_{it} = \theta + \sum_k \beta_k \, Shocks_{kit} + \gamma FEFL_{it} + \sum_k \rho_k \, Shocks_{kit} \cdot \; FEFL_{it} + \tau_{it}' \boldsymbol{\alpha} + c_i + u_{it} \qquad (9)$$

where y_{it} is the variable measuring portfolio quality or profitability of the MFI *i* in period *t.* The variables of rainfall shocks are named *Shocks*, the subscript $k = \{1,2\}$ identifies the two different seasons. The variable *FEFL* is the proxy for costs of funds, and measures financial expenses for funding liabilities weighted by gross loan portfolio. The matrix τ_{it} contains the set of controls.

[8] During the year-sample, FEFL shows a stable behavior in Mexico, in Peru and Ecuador ir is possible to observe an increasing cost tendency. See Table A4 and Figure A1 in Appendix section.

[9] All monetary values are expressed in real terms. Inflation rates come from the World Bank whereas Gross Domestic Product (GDP), Gross National Income (GNI), and planting areas from national economic and agricultural agencies of each country as described in section 4.

Unobserved fixed effects such as risk aversion and entrepreneurship ability of the lenders are represented by c_i and the error term is u_{it}. The answer to the first question arises from the coefficient estimates, β, and to the second from the estimates of interaction terms, ρ.

The first set of regressions is run as stated in (9). Next, to address endogeneity between the financial variables of interest, the same model is estimated using the lags of the variables as instruments in a second set of regressions. The estimates from these static models will provide initial responses to the research questions, however, the dynamism in MFIs choices described in the theoretical model will be left out. This matters because the lending and borrowing choices in current periods can be driven by the financial performance in previous periods. Alternatively, a third set of regressions is run within a dynamic panel data framework. This will help us to capture time-dependence of financial performance and the dynamic choices of the MFIs. Here the estimations will be carried out applying the Generalized Method of Moments (GMM) suggested by Arellano and Bond (1991), using lagged differences as instruments. The three set of results for the estimates of portfolio quality are shown in Table 2 and of profitability in Table 3.

Effects of Rainfall shocks on Portfolio Quality

Consider first the estimates of the effects of seasonal rainfall shocks on PAR30 in Table 2. The results indicate that rainfall shocks during the winter season have statistically significant effect. This result is positive and robust to the three different specifications. It means that rain above the mean increases the portfolio at risk over 30 days. For example, assuming the financial expenses are zero, when deviations of precipitation with respect to the mean increase in 1 mm, the outstanding balance of loans with arrears over 30 go up by 0.72 points. Hence, an increase in 1 mm by standard deviation of 1.642 (table 2) would increase PAR30 by 0.2 percent.

Results for PAR90, LLR and WOR, do not show a robust effect due precipitation. These results could reflect that MFIs are able to internalize the climate exposure of their credit applicants in their analyses of credit risk. i.e., resilience on delinquency variables is indicative of possible *ex-ante* hedging strategies.

Table 2. Effects of precipitation shocks on indicators of portfolio quality (PAR30, PAR90, LLR and WOR)

	OLS FE				IV OLS FE				GMM			
Dependent Variable	**PAR30**	**PAR90**	**LLR**	**WOR**	**PAR30**	**PAR90**	**LLR**	**WOR**	**PAR30**	**PAR90**	**LLR**	**WOR**
L1									0.246 **	0.352 ***	-0.167	-0.195
Shock Summer	-0.0023	-0.122	0.1342	0.1898	0.071	-0.1458943	-0.158	-0.040	0.0723	-0.2607	0.0165	0.2938
Shock Winter	1.0792 **	0.769 **	0.105	-0.123	0.658 **	0.605 **	0.4506 **	0.357	0.720**	0.396	-0.1020	-0.3657
FEFL/GLP (%)	-0.194	-0.1522	0.1445	0.2645 **					-0.0315	-0.0032	0.1003	0.2128
FEFL/GLP_ L1 (%)					-21.8564 *	-17.452 **	-18.4916 **	-13.989 *				
Shock Summer*FEFL/GLP	0.0194	0.0096	-0.0375**	-0.0363 **					-0.0078	0.0076	-0.0253	-0.0369
Shock Winter*FEFL/GLP	-0.1687 **	-0.116 *	-0.0129	0.0362					-0.100 **	-0.0353	0.0104	0.0542
Shock Summer*(FEFL/GLP)_L1					0.0063	0.0059	0.0079	0.0057358				
Shock Winter*(FEFL/GLP)_L1					-0.0976 *	-0.0887 *	-0.0848 **	-0.0603				
Number of observations	235	235	235	235	234	234	234	234	141	141	141	141
R2-W	0.1682	0.0973	0.746	0.2981	0.1638	0.137	0.151	0.1421				
R2- B	0.0584	0.03399	0.002	0.0244	0.0736	0.0003	0.0003	0.0848				
R2-O	0.0737	0.2661	0.0048	0	0.819	0.0081	0.0052	0.0174				
Prob > F	0.0075	0.0014	0	0	0.0105	0.0507	0.0232	0.0388				
GMM												
Prob > F									0	0	0.0064	0.003
Arellano-Bond test AR(1)									0.099	0.043	0.125	0.094
Arellano-Bond test AR(2)									0.384	0.296	0.269	0.25
Hansen test of overid. restrictions: Prob > chi2									1	1	0.995	0.993

Notes:

1) The term Financial Expenses for Funding Liabilities (FEFL) is weighted by Gross Loan Portfolio (GLP), yielding "FEFLGLP". The lagged terms refer to "FEFL_L1".
2) In the IV OLF FE specification, the interaction term variables between precipitation shocks with Financial Expenses for Funding Liabilities include the term FEFL that is lagged one period (FEFL_L1).
3) The terms Equity and Borrowings are terms weighted by Gross Loan Portfolio.
4) "Equity_ L1" (%), refer the variable Equity weighted by Gross Loan Portfolio (GLP), lagged one period.

Table A1

To summarize, the results so far demonstrate that the measure of portfolio risk at 30 days is statistically determined by the occurrence of extreme values of precipitation. This is a straight solution to the first research question and serves to validate the assumption in the theoretical model that systemic events negatively affect repayment rates. To answer the second research question we verify whether the inverse relationship is conditioned on the cost of funds using the estimates of the interaction terms between rainfall shocks and FEFL.

Table 2 shows that the estimates of the interaction between shocks in the season winter and FEFL for PAR30 are statistically significant and robust to all specifications. The negative signs indicate that higher cost of funds indeed ameliorate the magnitude of the effect of the rainfall shocks on PAR30. For example, when FEFL is zero, a one unit increase in the shock (that is, one mm of rainfall above the mean) increases PAR30 in 0.2 percent, but when FEFL is at the mean value (7.05)[10], the same one unit increase in the shock increases PAR30 to 0.17 only, i.e., the effect of the shock is less severe when the funding costs are higher.

Effects of Rainfall Shocks on Profitability

In line with the previous results and with the theoretical setup, extreme rainfall is expected to influence MFIs' profitability. The econometric results in Table 3 support the premise. For the winter season, they show that annual returns on equity are statistically sensitive to precipitation shocks and robust in the three model specifications. As the relationship is direct, the results imply that the profitability of the MFIs declines, the more the precipitation level deviates above the mean. These variables remain statistically relevant when interacted with

[10] Please refer to table A3 in Appendix section.

FEFL, but with reversed sign. The implication is consistent with the theoretical findings, that is, higher costs of funds lessen the magnitude of the precipitation shocks on profitability.

Table 3. Effects of precipitation shocks on Return on Equity (ROE)

Dependent Variable	OLS FE	IV OLS FE	GMM
L1			-0.1630 **
Shock Summer	5.325 ***	-1.627	-2.478
Shock Winter	-16.754***	-7.845 ***	-10.447 ***
FEFL/GLP (%)	3.4844 ***		-4.227 ***
FEFL/GLP_ L1 (%)		-0.6667	
Shock Summer*FEFL/GLP	-0.9071 ***		0.324 *
Shock Winter*FEFL/GLP	3.2834 ***		1.884 ***
Shock Summer*(FEFL/GLP)_L1		0.1218 ***	
Shock Winter*(FEFL/GLP)_L1		1.6453 ***	
Number of observations	235	234	141
R2-W	0.3532	0.5577	
R2- B	0.0111	0.1209	
R2-O	0.0601	0.2633	
Prob > F	0	0	
GMM:			
Prob > chi2			0
Arellano-Bond test AR(1)			0.06
Arellano-Bond test AR(2)			0.137
Hansen test of overid. restrictions: Prob > chi2			1
Notes: Idem			

The theoretical explanation for the previous remark comes from equation (7) which showed that *ceteris paribus*, an MFI with relatively higher costs of extra funds would optimally increase profitability by lowering the effect of the systemic shocks on repayment rates. This means that generation of sustained profits for MFIs facing comparatively higher costs of funds, will require the implementation of lending strategies that reduce the impact of systemic events on loan risk.

Conclusions

The capacity of agricultural microfinance institutions to generate sustained revenues is highly reliant on weather conditions, and the recent commercial orientation experienced in the microfinance industry could further undermine it, due to their comparatively stronger dependence on governments and donors funding. This paper adds nuance to our understanding of how systemic events are transmitted to microfinance institutions that lend to agricultural producers by investigating two interlinked hypotheses. The first hypothesis suggests a close relationship between the occurrence of rainfall shocks and the portfolio quality and profitability of the MFIs. The second, proposes that such relationship is not independent of financial expenses, but that the degree of resilience or susceptibility of the financial indicators is influenced by the costs of funds instead.

In order to validate these premises, we constructed a unique longitudinal dataset at the MFI level employing financial information from a set of institutions in Ecuador, Mexico, and Peru, rainfall data from the nearest agricultural settlements and weather stations for each one of the institutions, and domestic macroeconomic indicators of the three countries. The first hypothesis was tested by estimating the effect of rainfall shocks on the quality of loan portfolio and profitability, where loan portfolio quality uses indicators of delinquency (loan loss ratio, LLR, and write-off ratio, WOR) and of risk (Portfolio at Risk over 30 days, PAR 30, and Portfolio at Risk over 90 days, PAR 90), whereas profitability was represented by the rate on equity (ROE).

The empirical results come from different econometric model specifications. The first set of regressions run a simple fixed effects models. Next, to address endogeneity between the financial variables of interest, the same model was estimated using lagged variables as instruments. A third set of regressions was run within a dynamic panel data framework. This allowed us to capture time-dependence of financial performance and the dynamic choices of the MFIs.

The results demonstrate a resilience on financial measures to rainfall shocks. This implies that the amount of uncollectable loans is influenced by the occurrence of shocks, in turn, it could reflect an effective use of *ex ante* hedging strategies as the indicators of default are not statistically significant to the occurrence of rainfall shocks. This means that extreme precipitation indeed undermines the quality of loan portfolios by increasing the outstanding balance of loans with arrears. The latter is in line with the estimates of profitability that showed that the ROE is also significantly sensitive to precipitation shocks. Because the published evidence on the actual effect of weather shocks on the financial performance of the MFIs is still scant, these results serve researchers and practitioners to better understand the exposure of MFIs to systemic events and then develop hedging instruments.

To test the second hypothesis, we incorporated financial expenses on funding liabilities (FEFL) as a proxy for cost of funds in the econometric estimations. The results lead us to conclude that the extent of the effect of precipitation shocks on the quality of the loan portfolio is not independent of the cost of funds. In particular, we found that the loan quality of an MFI with relatively low costs of funds is prone to suffer more the occurrence of the shocks than the loan quality of an MFI with higher costs. The empirical results cannot be used to demonstrate a causal relationship, but they are consistent with our theoretical derivations, showing that the costs of funds have a significant influenced on how profitability of the MFI respond to the shock. An MFI that is constrained by relatively high costs of funds implements lending strategies that better isolate the impact of systemic events on loan risk in order to generate profits. In contrast, the occurrence of the systemic shock will have less influence on the types of lending strategies employed by an MFI with relatively low cost of funds as it does not constraint its capacity to generate profits.

Results from this work can aid practitioners to create strategies to build sustainable lending institutions. Our findings show magnitude and channels through which weather shocks can affect their financial operations. More generally, these results may also help in the design of funding policies that facilitate the financial development of agricultural regions as, to our acknowledge, no published evidence documents the relationship between the costs of funds and the resilience of the MFIs to rainfall shocks.

Some limitations of our analysis should be acknowledged. The most important limitations are related to the availability of data. For instance, despite our attempts to address endogeneity between the financial variables of interests, we recognize that stronger instruments will benefit the estimations. The short time series employed also constrained our ability to generate other measures of rainfall shocks and further test the robustness of the results. Finally, the agricultural GLP proportion each MFIs manages would provide more accuracy in the results. Despite the latest research in Latin-American MFIs, this updated information is little disclosed in all the MFIs of the sample. Despite these limitations, we are confident about the soundness of the theoretical and empirical methods applied. Our main results contribute to the development literature focused on investigating mechanisms for the efficient provision of financial services to the rural poor.

References

Adams, D. W., & Von Pischke, J. D. (1992). Microenterprise credit programs: Déja vu. *World Development*, 20(10), 1463-1470.

Adams, D. W., & Vogel, R.C. (2014). Microfinance approaching middle age. *Enterprise Development and Microfinance*, 25(2), 103-115.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies,* 58(2), 277–297.

Baquero, G., Hamadi, M., & Heinen, A. (2012). Competition, loan rates and information dispersion in microcredit markets. *LSF,* Working Paper Series No. 11-17.

Bhanot, D., & Bapat, V. (2015). Sustainability index of micro finance institutions (MFIs) and contributory factors. *International Journal of Social Economics,* 42 (4), 387 – 403.

Biekpe, N., & Kiweu, J.M. (2009). Leveraging donor funds: the switch to commercial funding. *Managerial Finance*, 35 (12), 1011 – 1026.

Byerlee, D., De Janvry, A., Sadoulet, E., Townsend, R., & Klytchnikova, I. (2008). *World Development Report 2008: Agriculture for Development*. World Development Report; no. 30. Washington, DC: World Bank Group.

Calderón, R. (2005). La banca de desarrollo en América Latina y el Caribe. *CEPAL. United Nations. Santiago de Chile*, Serie 157. 44 pags.

Castellani, D., & Viganò, L. (2017). Does willingness-to-pay for weather index-based insurance follow covariant shocks?. International Journal of Bank Marketing, 35(3), 1-43.

Cheng, E., & Ahmed, A.D. (2014). The demand for credit, credit rationing and the role of microfinance. Evidence from poor rural countries of China. *China Agricultural Review*. 6(2), 295-315.

Collier, B., Katchova, A.L., & Skees, J. R. (2011). Loan portfolio performance and El Nino, an intervention analysis. *Agricultural Finance Review*, 71(1), 98-119.

Conning, J. (1999). Outreach, sustainability and leverage in monitored and peer-monitored lending. *Journal of Development Economics,* 60(1), 51–77.

Conning, J., & Morduch, J. (2011). Microfinance and Social Investment. *The Annual Review of Financial Economics,* 1(3), 407-434.

Cull R., Demirgüc-Kunt A., & Morduch, J. (2007). Financial performance and outreach: a global analysis of leading microbanks. *The Economic Journal,* 117.517, F107-F133.

Cull R., Demirgüc-Kunt A., & Morduch, J. (2009). Microfinance Meets the Market. *Journal of Economic Perspectives,* 23 (1), 167-192.

Cull R., Demirgüc-Kunt A. & Morduch, J. (2014). Banks and Microbanks. *Journal of Financial Services Research* 46: 1-53.

Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics,* 96(2), 159-173.

Dupas, P, & Robinson, J. (2013). Saving constraints and microenterprise development: evidence from a field experiment in Kenya. *American Economic Journal: Applied Economics,* 5(1), 163-192.

FAO. Food Agriculture Organization of the United Nations. (2015). *The impact of disaster on agriculture and food security*. Retrieved from: http://www.fao.org/3/a-i5128e.pdf

FAO. Food Agriculture Organization of the United Nations. (May, 18th, 2013). La sequía causa pérdida en la producción del maíz en Ecuador. *Agronoticias Latin America &*

The Caribbean. Retrieved from: http://www.fao.org/agronoticias/agro-noticias/detail/en/c/176406/

Giné X., & Yang, D. (2009). Insurance, credit, and technology adoption: field experimental evidence from Malawi. *Journal of Development Economics,* 89 (1), 1–11.

Gosh, S., & Van Tassel, E. (2011). Microfinance and competition for external funding. *Economic Letters*, 112(2), 168–170.

Hazell, P. B. R. (1992). The appropriate role of agricultural insurance in developing countries. *Journal of International Development,* 4(6), 567–581.

Hermes, N., Lensink, R., & Meesters, A. (2011). Outreach and efficiency of microfinance institutions. *World Development,* 39(6), 938–948.

IFAD (International Fund for Agricultural Development). (2011). Rural Poverty Report 2011. *Rome: IFAD.* Retrieved from: https://www.ifad.org/topic/overview/tags/rpr

Iturrioz, R., & Arias, D. (2010). Agricultural insurance in Latin America. Developing the Market. The World Bank. Report no. 61963-LAC, 1, 1-152.

Le Saout, E., & Daher, L. (2016). Microfinance Performance in Financial Markets: The Case of Microfinance Investment Vehicles. In David Crowther, Linne Marie Lauesen (Ed.), *Accountability and Social Responsibility: International Perspectives (Developments in Corporate Governance and Responsibility, Vol 9, (pp101-123).* Emerald Group Publishing Limited.

Mahul, O., & Stutley. C. (2010). Government Support to Agricultural Insurance: Challenges and Options for Developing Countries. *Washington, DC: World Bank*. Retrieved from: https://openknowledge.worldbank.org/handle/10986/2432

Maystadt, J., Ecker, O. (2014). Extreme weather and civil war: Does drought fuel conflict in Somalia through livestock price shocks?. *American Journal Agricultural Economics,* 96*(*4), 1157-1182.

McIntosh, C., & Wydick, B. (2005). Competition and microfinance. *Journal of Development Economics*, 78(2), 271-298.

Miller, C., Ritcher, S., McNellis, P. & Mhlanga, N. (2010). Agricultural investment funds for developing countries. *FAO. Food Agriculture Organization of the United Nations, Rome.*

Miranda, M. J., & Farrin, K. (2012). Index insurance for developing countries. *Applied Economics Perspectives and Policy,* 34(3), 391-427.

Miranda, M. J., & González-Vega, C. (2011). Systemic risk, index insurance and optimal management of agricultural loan portfolios in developing countries. *American Journal of Agricultural Economics,* 93(2), 399–406.

Maystadt, J.-F., & Ecker, O. (2014). Extreme weather and civil war: Does drought fuel conflict in Somalia through livestock price shocks?. *American Jounral Agricultural Economics, 96(4),* 1157-1182.

MIX Market. Microfinance Information Exchange (2017). Glossary. Available at: https://www.themix.org/glossary

Mosley P., & Hulme, D. (1998). Microenterprise finance: Is there a conflict between growth and poverty alleviation?. *World Development,* 26(5), 783-790.

Nagy, G.J., Caffera, R.M., Aparicio, M., Barrenechea, P., Bidegain, M., Giménez, J.C., Lentini, E., Magrin, G., Murgida, A.M., Nobre, C., Ponce, A., Travasso, M.I., Villamizar, A. and Wehbe, M. (2006). Understanding the potential impact of climate change and variability in Latin America and the Caribbean. Stern Report Draft. Research report prepared for the stern review on the economics of climate change.

Tyndall Centre for Climate Change Research. Report number: 1, Affiliation: Facultad de Ciencias, UdelaR, Montevideo, Uruguay.

Navajas, S., Conning, J., & Gonzalez-Vega, C. (2003). Lending technologies, competition and consolidation in the market for microfinance in Bolivia. *Journal of International Development*, 15(6), 747-770.

Odening, M., & Zhiwei, S. (2014). Challenges of insuring weather risk in agriculture. *Agricultural Finance Review*, 74(2), 188-199.

Pelka, N., Musshoff, O., & Weber, R. (2014). Does weather matter? How rainfall affects credit risk in agricultural microfinance. *Agricultural Finance Review*, 75(2), 194-212.

Skees, J., Goes, A., Sullivan, C., Carpenter, R., Miranda, M., & Barnett, B. (2006). Index insurance for weather risk in lower-income countries. *USAID Microenterprise Development (MD) Office, USAID/DAI. Rural Finance Market Development, Washington, DC.*

Turvey, C. G. (2001). Weather derivatives for specific event risks in agriculture. *Applied Econonomic Perspectives and Policy*, 23 (2), 333-351.

Von Pischke, J.D. (1996). Measuring the trade-off between outreach and sustainability of microenterprise lenders. *Journal of International development*, 8(2), 225-239.

Von Stauffenberg, D., Jansson, T., Kenyon, N., & Barluenga-Badiola, M. (2003). *Performance indicators for microfinance institutions: Technical guide (3rd Edition).* CGAP MicroRate and Inter-American Development Bank, Washington, DC.

Wenner, M. (2005). Agricultural insurance revisited: new developments and perspectives in Latin America and the Caribbean. Washington, D,C: *Interamerican Development Bank.* Retrieved from: https://www.microfinancegateway.org/library/agricultural-insurance-revisited-new-developments-and-perspectives-latin-america-and

The World Bank Group. (2010). Agricultural Insurance on Latin America. Developing the Market. Report no. 61963-LAC. Retrieved from: http://documents.worldbank.org/curated/en/179701468277786453/Agricultural-insurance-in-Latin-America-developing-the-market

The World Bank Group. (2017). Climate Change Knowledge Portal for Development Practitioners and Policy Makers. Retrieved from: http://sdwebx.worldbank.org/climateportal/index.cfm?page=global_map_region&ThisMap=LA

Trivelli, C., & Venero, H. (2007). Banca de desarrollo para el agro: experiencias en curso en América Latina. Instituto de Estudios Peruanos, Serie: Análisis Económicos, 25, 1-375.

Yaron, J. (1994). What makes rural finance institutions successful?. *The World Bank Research Observer*, 9(1), 49–70.

APPENDIX

Dependent variables

- **PAR30.-Portfolio at Risk > 30 days Ratio (%):** Portfolio at Risk > 30 days/ Loan Portfolio, gross.
- **PAR90: Portfolio at Risk > 90 days Ratio (%):**Portfolio at Risk > 90 days/ Loan Portfolio, gross.
- **LLR (Loan Loss Rate, %)**: (Write-offs - Value of Loans Recovered)/ Loan Portfolio, gross, average
- **WOR (Write or ratio, %)**:Write Offs / Loan Portfolio, gross, average
- **ROE (Return on Equity, %):** Net Income/Shareholders' Equity.

Independent Variables

From the MIX Market:

- GLP (Gross Loan Portfolio in million dollars).
- GLP-Assets: GLP to total assets: GLP/Total assets.
- Equity (MUSD). Equity measured in Millions dollars.
- Equity/GLP (%). Equity measured in Millions dollars weighted by GLP.
- Deposits to loans: Deposits/GLP
- Borrowings/GLP (%).
- Deposits: Total value of all deposits account
- FEFL: Financial expense on funding liabilities: All costs incurred in raising funds from third parties including deposits, borrowings, subordinated debt and other financial obligations in addition to fee expenses from non-financial services. Proxy of Funding Costs.
- FEFL/GLP: Financial expense on funding liabilities weighted by GLP.
- Profit (loss) /GLP (%): The total income minus expenses, excluding the components of other comprehensive income, in millions Dollars; weighted by GLP.
- Borrowers per loan officer: Number of active borrowers (clients) per loan officer at the organization as of the end of the reporting period.
- Debt to equity (%): Total Liabilities / Total Equity

- Average loan balance per borrower/GNI (%): Average loan balance per borrower/GNI per capita. Adjusted Average Loan Balance per Borrower/ GNI per Capita

From the World Bank

- Interest Rate loans: Lending Interest Rate (%): Bank´s rate to meet the short- and medium-term financing needs of the private sector.
- Inflation: Inflation, consumer prices (annual %).
- Historical average monthly rainfall values. (mm). Monthly average values for each selected area. Data generated by the Climate Change Knowledge Portal.

From other sources:

- GDP dep millions USD: Local GDP: Agricultural gross domestic product from locations where the MFIs runs their main agricultural operations.
- Planting area: In Hectares.
- Rain precipitation: seasonal precipitation measured in mm:
  Summer: Summer &Autumn seasons. For Peru, from December to April; Mexico: June to November; Ecuador: October to May.
  Winter: Winter & Spring seasons. Peru: May to November; Mexico: December to May; Ecuador: June-September.
- Interaction Variables: Shock precipitation seasons interacted with FEFL (this latter, weighted by GLP).
  Shock Summer*FEFL. Interaction term Difference in precipitation in summer with FEFL.
  Shock Winter*FEFL. Interaction term Difference in precipitation in winter with FEFL.

Table A1. Panel data results on portfolio quality variables. Three estimation methods: Fixed Effects; Fixed effects on endogenous variables and Generalized Method of Moments (GMM)

	OLS FE				**IV OLS FE**				**GMM**			
Dependent Variable	**PAR30**	**PAR90**	**LLR**	**WOR**	**PAR30**	**PAR90**	**LLR**	**WOR**	**PAR30**	**PAR90**	**LLR**	**WOR**
L1									0.246 **	0.352 ***	-0.167	-0.195
Shock Summer (mm)	-0.0023	-0.122	0.1342	0.1898	0.071	-0.1458943	-0.158	-0.040	0.0723	-0.2607	0.0165	0.2938
Shock Winter (mm)	1.0792 **	0.769 **	0.105	-0.123	0.658**	0.605 **	0.4506 **	0.357	0.720**	0.396	-0.1020	-0.3657
FEFL/GLP (%)	-0.194	-0.1522	0.1445	0.2645 **					-0.0315	-0.0032	0.1003	0.2128
FEFL/GLP_ L1 (%)					-21.8564 *	-17.452 **	-18.4916 **	-13.989 *				
Shock Summer*FEFL/GLP	0.0194	0.0096	-0.0375**	-0.0363 **					-0.0078	0.0076	-0.0253	-0.0369
Shock Winter*FEFL/GLP	-0.1687 **	-0.116 *	-0.0129	0.0362					-0.10004 **	-0.0353	0.0104676	0.0542
Shock Summer*(FEFL/GLP)_L1					0.0063	0.0059	0.0079	0.0057358				
Shock Winter*(FEFL/GLP)_L1					-0.0976 *	-0.0887 *	-0.0848 **	-0.0603				
Equity/GLP (%)	0.0282	0.0170	-0.0534 ***	-0.0550 ***					0.066 ***	0.0411 *	-0.0913 **	-0.0966 **
Equity/GLP_L1 (%)					-0.0072381	-0.0035	0.0049	0.0040				
Borrowings/GLP (%)	0.0029	-0.0204	-0.065 ***	-0.064 ***	-0.0100	-0.0242 **	-0.0430 ***	-0.0417***	-0.00645	0.023	-0.0735 **	-0.0795 **
Lending interest rate (%)	-0.2411	0.0263	-0.0212	-0.1058					-0.5363 *	-0.533 **	-0.1245	-0.147
Lending interest rate_L1 (%)					-0.0377	-0.0552	0.0191	0.0226				
log GDP	2.3871	0.8575 *	0.5036	0.5077	1.840	1.1312 **	-0.0312	-0.3159	3.5335 *	3.256 *	2.6848	1.8412
Planting area (Mha)	-1.884	-1.2780	-0.3724	-0.2895	-1.5171	-1.0638	-0.2263	-0.2276	-0.8647	-0.6507	-0.6892	-0.6671
Harvest area (Mha)	-8.354**	-2.763	0.7329	0.595	-9.551 ***	-3.7391 *	1.8956	1.8406	-3.932***	2.188 **	0.7468	0.1919
Average loan balance per borrower/GNI (%)	-0.0274	0.0014	0.0258	0.0264	-0.0553 **	-0.0062	0.0162	0.0171	0.0036	-0.0065	0.0379	0.0406 **
t												
2012	0.3745	0.2067	0.3587	0.4278	0.4767	0.2773	0.3924	0.4844	-0.1790	0.5336	-0.3248	-0.0001
2013	0.3436	0.3000	0.7060	0.5244	0.4199	0.2367	0.8910 **	0.838 **	-0.8272	0.0261	-0.0951	0.0208
2014	0.2254	0.8529	0.7975	0.7467	0.395	0.736	1.002 **	1.150 ***				
2015	1.178	1.640 ***	0.4012	0.269	1.220 *	1.457 ***	0.390	0.4523	-0.7643 *	0.4719	-0.2969	0.4230
cons	-2.271	0.6418	0.727	0.9999	1.86	1.645	2.946	4.079				
Number of observations	235	235	235	235	234	234	234	234	141	141	141	141

R2-W	0.1682	0.0973	0.746	0.2981	0.1638	0.1372	0.151	0.1421				
R2- B	0.0584	0.03399	0.002	0.0244	0.0736	0.0003	0.0003	0.0848				
R2-O	0.0737	0.2661	0.0048	0	0.819	0.0081	0.0052	0.0174				
Prob > F	0.0075	0.0014	0	0	0.0105	0.0507	0.0232	0.0388				
GMM												
Prob > F									0	0	0.0064	0.003
Arellano-Bond test AR(1)									0.099	0.043	0.125	0.094
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8) "Equity_ L1" (%), refer the variable Equity weighted by Gross Loan Portfolio (GLP), lagged one period.

Table A1

Table A2. Panel data results on profitability variable. Three estimation methods: Fixed Effects; Fixed effects on endogenous variables and Generalized Method of Moments (GMM).

Dependent Variable	**OLS FE**	**IV OLS FE**	**GMM**
L1			-0.1630 **
Shock Summer (mm)	5.325 ***	-1.627	-2.478
Shock Winter (mm)	-16.754***	-7.845 ***	-10.447 ***
FEFL/GLP (%)	3.484 ***		-4.227 ***
FEFL/GLP_ L1 (%)		-0.667	
Shock Summer*FEFL/GLP	-0.907 ***		0.324 *
Shock Winter*FEFL/GLP	3.283 ***		1.884 ***
Shock Summer*(FEFL/GLP)_L1		0.1218 ***	
Shock Winter*(FEFL/GLP)_L1		1.6453 ***	
Equity/GLP (%)	-0.303 **		-0.194
Equity/GLP_L1 (%)		-0.0189	
Borrowings/GLP (%)	0.029	0.1593	0.319 *
Lending interest rate (%)	-1.327		-3.13 **
Lending interest rate_L1 (%)		0.126	
log GDP	13.571	-1.127	23.861 **
Sown area (Mha)	-0.987	-4.095	7.9128
Harvest area (Mha)	-18.895	-9.333	-14.007
Average loan balance per borrower/GNI (%)	0.369 **	0.1320	0.21
t			
2012	-7.467 **	-3.006	2.448
2013	-8.042 **	-2.186	0.9637
2014	-5.368	-2.212	
2015	-3.259	-1.864	-0.738
cons	-70.53	20.5992	
Number of observations	235	234	141
R2-W	0.3532	0.5577	
R2- B	0.0111	0.1209	
R2-O	0.060	0.2633	
Prob > F	0	0	
GMM:			
Prob > F			0
Arellano-Bond test AR(1)			0.06
Arellano-Bond test AR(2)			0.137
Hansen test of overid. restrictions: Prob > chi2			1
Notes. Idem			

Table A3. Summary Dependent and explanatory variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
PAR30 (%)	235	5.424	4.572	0.420	40.150
PAR90 (%)	235	4.045	4.095	0.000	36.830
LLR (%)	235	1.905	2.782	-3.050	16.850
WOR (%)	235	2.123	2.786	0.000	18.120
ROE (%)	234	9.634	19.676	-216.020	64.900
Shock summer	235	-25.644	85.324	-899.627	12.991
Shock winter	235	-178.437	651.339	-5263.193	6.472
FEFL/GLP * (%)	235	6.893	6.932	0.000	81.749
shock summer*FEFLGLP	235	-1.878	6.252	-65.717	0.930
shock winter*FEFLGLP	235	-21.885	187.457	-2837.071	0.492
Equity/GLP (%)	235	31.302	29.129	1.099	215.613
Borrowings/GLP (%)	235	35.380	34.239	0.000	103.796
Lending interest rate (%)	235	10.385	6.541	3.400	19.200
log GDP	235	5.611	1.435	2.865	8.161
Planting area (Mha)	235	0.262	0.421	0.002	1.570
Harvest area (Mha)	235	0.244	0.404	0.001	1.479
Average loan balance per borrower / GNI per capita (%)	235	44.419	31.349	1.300	124.770
Equity (MUSD)	235	20.786	33.645	0.203	140.901
Borrowings MUSD)	235	15.581	32.132	0.000	297.254
FEFL (MUSD)	235	7.055	11.224	0.000	50.132
GLP (MUSD)	235	121.741	218.580	0.601	1160.711
Agricultural local GDP (MUSD)	235	593.072	670.503	17.554	3500.493

Note: * FEFL/GLP: Financial expenses for funding liabilities weighted by gross loan portfolio. (%)

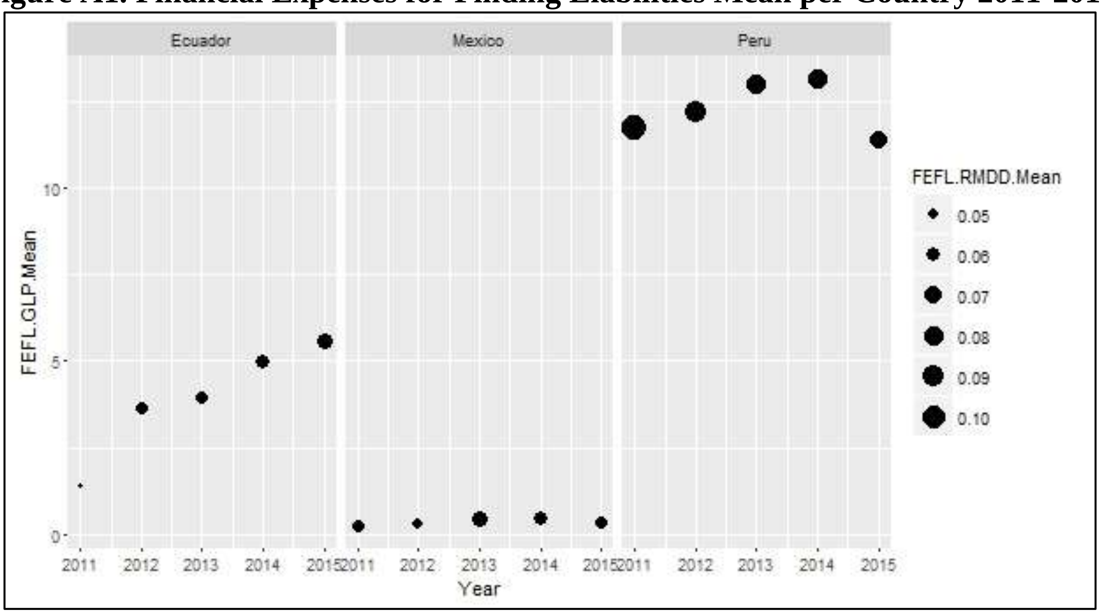
Source: Author's calculation using data from the MIX market, the World Bank, economic and weather domestic agencies..

Table A4. Financial Expenses Funding Liabilities Mean Values

Year	Country	Obs	Mean	SE Mean	StDev	Min	Max
2011	Ecuador	47	1.399	0.59	2.505	0	9.864
2011	Mexico	47	0.249	0.096	0.273	0	0.739
2011	Peru	47	11.74	2.88	13.21	0.03	45.57
2012	Ecuador	47	3.64	1.88	7.97	0.02	32.89
2012	Mexico	47	0.282	0.111	0.315	0	0.931
2012	Peru	47	12.2	2.95	13.5	0.03	47.67
2013	Ecuador	47	3.96	1.8	7.64	0.03	29.49
2013	Mexico	47	0.424	0.172	0.488	0.006	1.19
2013	Peru	47	13.02	3.04	13.92	0.04	49.22
2014	Ecuador	47	4.96	2.27	9.63	0.03	37.6
2014	Mexico	47	0.443	0.196	0.556	0	1.36
2014	Peru	47	13.18	3.15	14.43	0.02	50.13
2015	Ecuador	47	5.58	2.51	10.67	0.02	40.72
2015	Mexico	47	0.338	0.136	0.383	0.021	0.971
2015	Peru	47	11.38	2.58	11.8	0.02	40.98

Note: Financial Expenses on Funding Liabilities over Gross Loan Portfolio.
Source: Author’s calculation using data from the MIX market.

Figure A1. Financial Expenses for Finding Liabilities Mean per Country 2011-2015



Source: Author’s calculation using data from the MIX market.

Table A5. List of MFIs used in the empirical analysis

MFIs Name	Type	Country	GLP (USD) m	Deposits (USD) m	Assets (USD) m	Number of Active Borrowers '000	Number of Depositors '000
AMEXTRA**	NGO	Mexico	2.32	1.81	2.76	4.71	
ASOCIACIÓN ARARIWA***	NBFI	Peru	4.65	0	7.8		
CACMU***	Credit Union / Cooperative	Ecuador	18.2	11.19	22.65	4.5	22.19
CCC***	NGO	Ecuador	3.56	0	4	1.27	0
CMAC Arequipa***	NBFI	Peru	946.35	977.38	1289.89	273.69	785.39
CMAC CUSCO***	NBFI	Peru	502.18	488.62	618.96	120	347
CMAC Del Santa***	NBFI	Peru	46.13	53.96	65.31	28.11	29.66
CMAC Huancayo***	NBFI	Peru	577.85	448.07	630.13	216.16	353.92
CMAC Ica***	NBFI	Peru	195.76	193.21	252.46	67.63	129.21
CMAC Maynas ***	NBFI	Peru	91.19	95.28	120	34	101
CMAC Paita***	NBFI	Peru	48.98	50.46	63.53	25.1	48.45
CMAC Piura***	NBFI	Peru	601.26	703.55	852.4	142	660
CMAC Tacna***	NBFI	Peru	182.32	187.48	238.36	50.08	94.44
CMAC Trujillo***	NBFI	Peru	398.64	397.89	532.97	151.41	253.2
COAC Chone***	Credit Union / Cooperative	Ecuador	30.74	29.94	46.66	8.06	35.65
COAC Guaranda***	Credit Union / Cooperative	Ecuador	34.37	29.31	38.67	6.49	12.7
COAC Jardín Azuayo***	Credit Union / Cooperative	Ecuador	461.53	414.38	534.87	76.75	224.33
COAC La Benéfica***	Credit Union / Cooperative	Ecuador	14.18	9.39	15.96	5.05	12.62
COAC Mushuc Runa***	Credit Union / Cooperative	Ecuador	132.86	126.55	162.25	41.07	73.63
COAC Nueva Huancavilca***	Credit Union / Cooperative	Ecuador	3.82	3.30	4.51	2.34	10.66
COAC Padre Vicente***	Credit Union / Cooperative	Ecuador	1.54	0.78	1.82	0.75	1.83
COAC San Antonio***	Credit Union / Cooperative	Ecuador	17.18	12.79	19.9	3.62	6.8
COAC San José***	Credit Union / Cooperative	Ecuador	82.43	80.89	102.17	16.09	39.82

COAC Santa Anita***	Credit Union / Cooperative	Ecuador	7.55	5.07	9.57	3.69	16.72
COAC Virgen del Cisne***	Credit Union / Cooperative	Ecuador	13.87	11.28	16.66	5.68	21.78
CONSER***	NBFI	Mexico	2.2	0	3.75	6.17	0
COOPAC Norandino***	Credit Union / Cooperative	Peru	9.82	4.54	14.41	5.22	5.2
COOPAC Santo Cristo***	Credit Union / Cooperative	Peru	68.18	61.56	89.81	22.36	56.28
CRAC Los Andes***	NBFI	Peru	44.71	36.95	53.71	34.76	21.65
CrediAvance***	NBFI	Mexico	17.86	0.23	19.18	79.96	
EDPYME Acceso Crediticio***	NBFI	Peru	45.44	0	52.72	7.32	0
EDPYME Alternativa***	NBFI	Peru	27.73		33.28	31.78	
EDPYME Solidaridad***	NBFI	Peru	31.1	0	38.64	24.52	0
FACES***	NGO	Ecuador	25.22		31.64	14.48	
FINCA - PER***	NGO	Ecuador	4.85		6.21	14.44	
FOVIDA***	NGO	Peru	1.82	0	1.98	0.42	0
Financiera CIA	NBFI	Mexico	2.41	0.15	3.04	3.46	3.46
Financiera Confianza***	NBFI	Peru	446.68	297.05		213.15	485.38
Financiera Credinka (ex Financiera Nueva Vision) ***	NBFI	Peru	190.45	157.69	251.05	60.38	51.24
Fundación Espoir***	NGO	Ecuador	43.9		47.54	45.14	
GCM***	NBFI	Mexico	5.05	0	5.79	18.42	0
INSOTEC***	NGO	Ecuador	29.27		35.07	15.2	
Oportunidad Microfinanzas**	NBFI	Mexico	1.1	0.17	1.7	4.03	
Pichincha Microfinanzas**	NBFI	Ecuador	1100.09	668.26	1188.21	305.37	1136.72
ProExito***	NBFI	Mexico	3.59	0	3.84	9.05	0
VISIONFUND ECUADOR-FODEMI***	NGO	Ecuador	40.46	0.17	43.63	61.63	0.03
Vision Fund - MEX**	NBFI	Mexico	11.51		13.82	28.52	

Note. *2012 Data; **2014 Data; ***2015 Data.
Source: MIX market.