Does weather matter? How rainfall shocks affect credit risk in agricultural micro-finance

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Abstract

Small-scale farmers in developing countries are undersupplied with capital. Although microfinance institutions have become well established in developing countries, they have not significantly ex-tended their services to farmers. It is generally believed that this is partly due to the riskiness of lending to farmers. This paper combines original data from a Madagascan microfinance institution with weather data to estimate the effect of rainfall on the repayment performance of loans granted to farmers. Results estimated by linear probability models and a sequential logit model show that excessive rain in the harvest period increases the credit risk of loans granted to farmers.

1. Introduction

Approximately 1.2 billion people worldwide are classified as extremely poor (UNDP, 2013). Moreover, around 75% of the people who are affected by poverty live in rural areas (FAO, 2002; Worldbank, 2012), and most of them are operating a farm business. The advancement of conditions in private entrepreneurship within the agricultural sector of developing countries is, therefore, an important starting point in the fight against poverty. This requires feasible investment opportunities and access to capital.

Microfinance institutions (MFIs) in developing countries focus on the provision of financial services for micro, small, and medium-sized enterprises (Godquin, 2004). Since the foundation of the first Grameen Bank in Bangladesh in 1983, microfinance has undergone an intense development process. The Grameen Bank was the first bank which offered group-based microcredit to the impoverished without requiring collateral. It is assumed that in 2010 approximately 137.5 million people worldwide made use of micro-credits. The number of micro-borrowers increased from 1997 to 2012 by 1,307%, indicating enormous growth in this sector (Maes and Reed, 2012). Nevertheless, different studies (e.g., Andrews, 2006; Hartaska and Holtmann, 2006; Christen and Anderson, 2013) indicate that not everybody has the same opportunities for accessing microcredit. There are numerous examples of successful MFIs in developing countries, but their loan portfolios consist primarily of loans to urban businesses. MFIs have not made much progress towards approaching farmers as potential clients. Consequently, the agricultural sector is still undersupplied with financial capital (Cabannes, 2012). A major problem for those who are financially excluded is their exposure to risk, which from a financial institution's perspective, makes lending to them difficult (Beck et al., 2006; Diagne et al., 2000; Foltz, 2004; Simtowe et al., 2008; Weber and Musshoff, 2012).

Weather risks in agricultural production are assumed to be a main driver of the risk in agricultural lending (Giné and Yang, 2009; Miranda and Gonzalez-Vega, 2011; Weber and Musshoff, 2012). In many developing countries, weather risk is substantial. Weather risks influence the profitability of the agricultural production and increase the volatility of the annual cash flow (Binswanger and Rosenzweig, 1986). This jeopardizes the small-scale farmers' capacity to handle their installment payments in due time. Accordingly, weather shocks are assumed to render the agricultural loan portfolios of financial institutions considerably riskier than urban business loan portfolios (Giné and Yang, 2009; Miranda and Gonzalez-Vega, 2011). However, there is little rigorous empirical evidence on the effect of idiosyncratic or aggregate shocks on financial outcomes in microfinance. Our study considers original lending data provided by a Madagascan MFI and investigates the possibilities of weather variations affecting the repayment performance of loans granted to small-scale farmers. Thus, this study is an important first step towards providing conclusive econometric evidence.

Our investigations focus on Madagascar as its economic structure displays the typical features of developing countries (Minten et al., 2009). In Madagascar, the agricultural sector is the second most important economic sector, representing 35% of the gross domestic product, and being mainly undertaken on the subsistence level (FAO, 2013). The area of investigation within Madagascar is characterized by wet rice agriculture in terrace cultivation.

We estimate linear probability models (LPMs) and a sequential logit model (SLM), which is also referred to as a sequential-logistical regression. The repayment performance of loans granted to small-scale farmers serves as the dependent variable in our models. From an MFI perspective, the repayment performance of loans is indicated by whether installments are made on time. Therefore, a high repayment performance indicates a low credit risk and vice versa. In order to describe the repayment performance of agricultural loans, weather indices have to be specified to serve as the independent variables that are of interest for our estimations. We carry out a correlation analysis between collected weather records and credit risk, and then compare these results with important weather risks from a crop farming perspective in the area of investigation. Aside from the weather indices, loan attributes and client characteristics are used as further independent variables in our models.

To our knowledge, this is the first study that combines original loan repayment data from a Madagascan MFI with weather data to estimate the effect of weather events on the repayment performance of loans granted to farmers. Furthermore, to our knowledge, this is the first study that uses a two-step estimation approach based on LPMs and an SLM to investigate the repayment performance in agricultural lending.

Hedging instruments like weather index-based insurances are discussed in agricultural and developing economic literature, as well as in practical development cooperation. The returns from weather index-based insurances are determined by means of objectively measurable weather variables that form the index of the insurance, such as the amount of precipitation during a period relevant for growth or the harvest period. These instruments may be used to transfer a specific part of the risk in agricultural lending to other markets (Brown, 2000; Skees and Barnett, 2006; Skees et al., 2007; CGAP, 2008; Skees, 2008a; Skees, 2008b; Giné and Yang, 2009; Miranda and Gonzalez-Vega, 2011). If we find a negative influence of weather variations on the repayment performance, weather index-based insurance may have the potential to mitigate a specific part of the risk in agricultural lending. Since weather index-based insurance is not affected by the problems of adverse selection and moral hazard, only low transaction costs are involved, which represents a key advantage over crop insurance (Coble et al., 1997; Goodwin, 2001; Berg and Schmitz, 2008). However, due to an imperfect correlation between the weather variable and the income, the hedging effectiveness of weather index-based insurance is diminished. On the one hand, apart from the insurance-related weather variable (e.g., precipitation in May), there may be other influencing weather factors (e.g., temperature in May) that lead to yield variations. In this context, literature often refers to the basis risk of production (Berg and Schmitz, 2008). On the other hand, there is a non-insurable difference between the weather events happening at the production site and those occurring at the reference weather station, which is referred to as geographical basis risk (Vedenov and Barnett, 2004).

The article is structured as follows: In the second section, we provide a literature review leading to our research hypotheses. The third section explains our assumptions and describes the databases we use. We describe our methodological procedure in section four. After the discussion of the results in the fifth section, the paper ends with conclusions and suggestions for future research.

2. Literature review and hypotheses

In many developing countries, efficient, privately owned MFIs were established since the early 1990s. They use lending techniques specifically adapted to poor entrepreneurs who are lacking collateral and proper business documentation. Many of these MFIs follow both commercial and social goals by providing microcredit to micro, small, and medium-sized enterprises. However, loan products for farmers can, despite their ability to reflect seasonality, barely deal with the risk present in agricultural production. Specific risks in agricultural production, as well as a lack of adequate risk-coping strategies (Binswanger and Rosenzweig, 1986; Llanto, 2007) might be the reason why financial institutions assume that lending to farmers might be more risky than lending to other sectors, especially in developing countries. Consequently, they are reluctant to approach farmers, which can lead to a lack of profitable investments in the agricultural sector (Field et al., 2011). While there are changes in the revenue levels due to fluctuating product prices, the literature considers weather-related agricultural yield risks to be the main cause for the comparatively high risk in agricultural lending (IPA, 2009). Weather risks affect the cash-flow variance more severely in agricultural than in non-agricultural enterprises.

The effect of weather-induced aggregate shocks on financial outcomes in microfinance has been widely discussed in theory, but rarely investigated empirically in either developing economic literature or in practical development cooperation (Brown, 2000; Skees and Barnett, 2006; Skees et al., 2007; CGAP, 2008; Skees, 2008a; Skees, 2008b; Giné and Yang, 2009; Miranda and Gonzalez-Vega, 2011, Berg and Schrader, 2012; Czura and Klonner, 2010). Czura and Klonner (2010) analyze the effect of the December 2004 Indian Ocean tsunami on credit demand and financial intermediation outcomes in the Rotating Savings and Credit Association in South India. They find an increase in the price of credit by 5% on average in the affected branch offices. Berg and Schrader (2012) analyze the effect of volcanic eruptions on loan default rates and interest rates of microfinance clients in Ecuador. They find that the probability to default increases for loans that have been approved after high volcanic activity. However, aside from rare respective empirical investigations, no investigations that focus on agricultural microfinance currently exist. Thus, given the weather risk exposition of farmers and, more specifically, the limited ability of small-scale farmers to deal with those uncertainties, the core hypothesis of our paper is: *Weather events significantly affect the repayment performance of loans granted to small-scale farmers in Madagascar.*

Many research studies prove that individual credit attributes, as well as socio-demographic characteristics affect the repayment performance of borrowers in developing countries (Njoku and Obasi, 1991; Morduch, 1999; Godquin, 2004; Roslan and Karim, 2009). Most financial institutions in developing countries offer rather standardized products, i.e., loans with fixed repayment schedules and loan repayments starting shortly after loan disbursement for both agricultural and non-agricultural enterprises. However, an investment needs some time to mature before first returns can be realized, which is a situation especially relevant for the agricultural sector (Binswanger and Rosenzweig, 1986). Therefore, some financial institutions are slowly starting to offer loans with grace periods, i.e. they allow shifting loan principal payments from month with low agricultural returns (e.g., growing period) to month with high agricultural returns (e.g., harvesting period). This is particularly relevant for agricultural entrepreneurs as such loans can take into account seasonal cash-flow patterns of farmers. This is also the case for the MFI investigated in this study. Consequently, 'grace periods' are an additional loan attribute that is considered in our estimation. Furthermore, self-selection is a well-known problem in the microfinance sector. The MFI can select or exclude potential clients based on their access to resources, skills, and so forth. On the one hand, farms that requested a loan without success are not represented in our model. On the other hand, farms that receive a loan and demonstrate good repayment performance have a better chance of receiving a second loan. We check for 'repeat clients' to eliminate bias effects on the results regarding risk differences between new and existing customers.

From an MFI perspective, Roslan and Karim (2009) and Godquin (2004) determine the following influencing factors on repayment performance of microcredit borrowers: age and gender of the loan borrower, number of family members and his or her work experience. Therefore, the second hypothesis of this study is the following: *Credit attributes and socio-demographic characteristics significantly affect the repayment performance of loans granted to small-scale farmers in Madagascar.*

3. Data

The basis of our analysis is a unique dataset with all loans disbursed by Accès Banque Madagascar (ABM), including loans to small-scale farmers. The ABM is a regulated and commercial bank which specializes in lending to micro, small, and medium-sized enterprises having mostly low loan collateral and only basic business documentation. Starting its business activities in Madagascar in 2007, the ABM is a continuously expanding bank. Meanwhile, the ABM runs 16 branch offices within the country, with the majority of their activities concentrated on a radius of 150 miles around the capital, Antananarivo, which is situated in the highland of the country. The dataset was extracted from the Management Information System (MIS) of the bank. It includes information regarding credit attributes (e.g., disbursed loan volumes, date of loan disbursement) and socio-demographic characteristics of the borrowers (e.g., age and gender). Furthermore, the dataset includes information relating to the branch office location and the year the loans were disbursed. Most of ABM’s loans (around 80%) are disbursed to non-agricultural entrepreneurs, as it is typically the case for MFIs in developing countries. In our analysis we considered a subset of these loans consisting of all 3,847 microloans disbursed by ABM and granted primarily to agricultural producers between February 2007 (foundation of the ABM) and February 2012 (month of data extraction) in the 16 branch offices existing in February 2012 (see Fig. 1). Thus, all loans investigated in this paper are used to finance agricultural activities (e.g., livestock, agricultural machinery, seedlings, and fertilizer). Loan data is automatically created by the MIS as soon as a loan is disbursed. The dataset was cleaned to correct for outliers and data input errors. Only loans with complete data were used. After data cleaning, 3,534 observations remained. The loan maturity was 195 days on average and did not exceed one year for any of the loans analyzed.

Daily precipitation data and daily temperature data from 2007 to 2012 are used from three weather stations, which are located in the area of investigation. The data is provided by the German Meteorological Service (DWD), which works in cooperation with a Madagascan meteorological service. The three weather stations of concern are located in Antananarivo (Ivato), Antsirabé, and Tamatave (Toamasina) (see Fig. 1). We assign each branch office to the weather station that is geographical closest to the respective branch office. The nine branch offices in Antananarivo, the branch office in Analavory and the branch office in Tsiroanomandidy are assigned to the weather station of Antananarivo. The distance between Antananarivo and Analavory is about 50 Miles, while there are about 95 Miles between Antananarivo and Tsiroanomandidy. The three branch offices in Antsirabé and the branch office in Ambatolampy (42 Miles) are assigned to the weather station of Antsirabé, and the branch office in Tamatave is assigned to the weather station of Tamatave.

[Insert Figure 1 here]

Farmers in our study are situated in the central highlands of Madagascar, which is characterized by wet rice agriculture. The farmers analyzed primarily grow rice in monoculture. Exceptionally, some farmers grow vegetables in addition to wet rice agriculture[1] in the area around the city of Antsirabé (one of the 16 branch offices). In the central highland of Madagascar, wet rice is cultivated in terraces, which requires the use of irrigation. In this country, rice is grown on approximately 800,000 hectares and is therefore the most important crop (Minten et al., 2009). In Madagascar, rice is grown on approximately 800,000 hectares and is therefore the most important crop (Minten et al., 2009). In September or October before the start of the rainy season, the fields are prepared for sowing. After the rainy season, the rice is harvested in March or April. The yield per hectare is comparatively low; a typical farmer produces one to two tons of rice per hectare while the national average is 1.84t/ha and this is well below the average yield of Asian rice farmers.

4. Methodology

In Section 4 (a), we define our dependent variable as 'credit risk' and we specify weather indices, which serve as the independent variables of substantial interest. In Sections 4 (b) and 4 (c), we describe the linear probability model and the sequential logit model used for the estimation of the repayment performance of

[1] Variant calculations show that including / excluding the branch office of Antsirabé does not have an effect on the coefficients of precipitation in our model.

loans granted to small-scale farmers.

4.1 Definition of credit risk and specification of weather indices

The repayment performance investigations are based on the credit risk of all loans in our dataset. Credit risk is defined as whether or not a borrower is able to pay back all loan installments by the due date. Hereby, four different credit risk indicators (CRI) are applied and used as dependent variables in our analysis. These indicators signify whether all loan installments were paid on time (CRI-0), at least one of the installments is overdue by one or more days (CRI-1), at least one of the installments is overdue by 30 or more days (CRI-30), and at least one of the installments is overdue by 90 or more days (CRI-90). These credit risk indicators are derived from the portfolio at risk (PAR), which is commonly applied in banking practice to indicate the share of a bank's loan portfolio that is overdue by a certain number of days on a specific date. For example, the Basel II regulations (the vast majority of central banks calls for the compliance with these regulations, even in developing countries) require the announcement of credit risk when a loan installment is at least 90 days overdue. Since installment payments in microfinance are mostly processed on a weekly or monthly basis and loan maturities are typically short, the portfolio at risk in microfinance is typically based on a 30 day overdue basis (Schreiner, 2000).

Existing studies relating to weather index-based insurances specify various weather indices differently. Frequent suggestions for temperature-based weather indices in the literature include so-called 'Heating-' and 'Cooling-Degree-Day-Indices' (Turvey, 2005). In contrast, the most important precipitation-based weather index is an accumulation index (cf., Stoppa and Hess, 2003; Berg and Schmitz, 2008). In the present study, an accumulation index is used, as it is easily applicable to every type of weather variable[2]. The accumulation index I_t^{ac} corresponds to the precipitation sum or the temperature sum within a certain accumulation period *x* in year *t*:

$$I_t^{ac} = \sum_{d=1}^{x} W_{d,t} \qquad (1)$$

whereby $W_{d,t}$ indicates the precipitation or the temperature on day *d* in year *t*. The precipitation and temperature data measured is summarized over all days of the accumulation period.

We choose a standardized weather index for all 16 branch offices. In the correlation analysis, periods of monthly accumulation of temperature and precipitation were tested. The correlation analysis between collected weather records and credit risk (CRI-1, CRI-30 and CRI-90) shows the highest correlations for the accumulated precipitation in March. The correlation coefficients are 0.65 (CRI-1), 0.49 (CRI-30) and 0.53 (CRI-90) for the precipitation sum in March and 0.63 (CRI-1), 0.48 (CRI-30), and 0.52 (CRI-90) for

[2] Correlation analyses for credit risk with an accumulation index (accumulated weather variable) and credit risk with an excess index (accumulated weather variable above a reference level / threshold) show higher correlations for the accumulation index.

the precipitation sum in April. The correlation coefficients for February are lower (0.54 for CRI-1, 0.23 for CRI-30, and 0.29 for CRI-90). This quantitative information is underlined by the fact that a very important weather risk of rice cultivation in the central highland of Madagascar is an excessive amount of rain in the harvest period (between the end of February to April), which reduces rice yields and, thus, leads to revenue losses for farmers (Minten and Barret, 2008). We also found correlations between temperature and rice yields. The correlation analysis between collected temperature records and credit risk (CRI-1, CRI-30 and CRI-90) revealed the highest correlations for the accumulated temperature in September and October, which are typically sowing months. The correlation coefficients are 0.27 (CRI-1), 0.30 (CRI-30) and 0.19 (CRI-90) for the temperature sum in September and 0.35 (CRI-1), 0.29 (CRI-30), and 0.24 (CRI-90) for the temperature sum in October.

Since we found higher correlation between precipitation and credit risk than for temperature and credit risk, the accumulated precipitation sums from February, March and April serve as standardized weather indices in our study. At the three weather stations examined, the average accumulated precipitation sum from February, March and April amounts to 258mm, 335mm and 195mm with a standard deviation of 157mm, 175mm and 133mm, respectively.

We analyzed the correlations between weather variables measured at the three reference weather stations. Results illustrated in table 1 show correlations between 0.69 and 0.78 for precipitation sums measured in March and between 0.97 and 0.99 for temperature sums measured in October, which are comparatively high.

[Insert Table 1 here]

4.2 Estimation of the repayment performance using a linear probability model (LPM)

In the first step of the analysis we check for separate effects of rain in different months (February, March and April) on the repayment performance of loans granted to small-scale farmers using a LPM[3]. The data of the three weather stations over a six-year period builds a pseudo-panel. The LPM can be written as (Hausman and McFadden, 1984):

$$Y^{*}_{i,j,t} = \alpha_{i,j,t} + \eta_t^{Y^*} + v_i^{Y^*} + \gamma_b^{Y^*} + \beta \cdot I_t^{ac} + \vec{X}_{i,j,t} + \varepsilon_{i,j,t} \qquad (2)$$

with $i = 1, \dots N, j = 1, \dots J, t = 1, \dots T$

and the observed variable,

$Y_{i,j,t} = 1\{Y^{*}_{i,j,t} > 0\}$.

In equation (2), the dependent variable $Y^{*}_{i,j,t}$ equals one if a loan borrower j is overdue with any of his or her installment payments of loan i that was taken up at time t. Otherwise, it equals zero. $\eta_t^{Y^*}$ are year fixed-

[3] A probit or logit model would be equally appropriate for estimating the effects of interst. Since the results are independent from the econometric model we chose (Berg and Schrader, 2012), we restrict our analysis to the LPM case because coefficients are easier to interpret.

effects, $v_i^{Y^*}$ are loan-specific fixed effects, and $\gamma_b^{Y^*}$ are branch-specific fixed-effects. I_t^{ac} describes the accumulated amount of precipitation in the respective accumulation period and $\vec{X}_{i,j,t}$ is a vector of control variables including different loan attributes and socio-demographic characteristics. Robust standard errors are clustered at the weather station level because residuals of all observations pertaining to the same measurement of a weather station are correlated. $\varepsilon_{i,j,t}$ stands for a normally distributed error term that is independent of i, j and t with a mean of zero and a variance of σ_u^2.

Our dependent variables are different credit risk indicators, which should be accessed stepwise. For example, an installment payment of a loan that is at least 90 days past the due date (CRI-90) has to go through the categories CRI-1 and CRI-30 first. The LPM does not take into account the gradual accessibility of the different default levels. Therefore, the LPM is only a pre-testing the effect separate effects of rain in different months.

4.3 Estimation of the repayment performance using a sequential logit model (SLM)

In a second step, we estimate an SLM for the month in which the simple linear probability model determines the highest impact (significance) of excessive rain on credit risk. Due to its structure, the SLM is particularly suited for response categories of the dependent variable, which can only be reached step by step (Hausman and McFadden, 1984; Wong and Mason, 1985; Tutz, 2005). However, in contrast to the LPM, the SLM does not allow for clustering standard errors at the weather station level. Therefore, a vector of dummy variables is added to the SLM to test for the influence of the weather station where the weather variable is measured. Nevertheless, a dummy variable is not able to capture the correlation of the observations pertaining to the same measurement of a weather station. In conclusion, we compare the results of both models.

SLMs are a special type of logistic regression models with categorical and ordinal-scaled dependent variables $Y_i \in \{i = 1, \dots, d\}$. Categorical regression models aim to estimate the conditional chance

$$\pi_r = P(Y = r), \qquad r = 1, \dots, d. \tag{3}$$

In equation (3), π_r describes the conditional probability for the category r. In the present study, we apply an SLM with ordered categories of d = 4. For the first category (Y_i = 1) all loans with a positive CRI-0 are applied. The second (Y_i = 2), third (Y_i = 3), and fourth (Y_i = 4) categories consist of all loans with positive CRI-1, CRI-30, and CRI-90, respectively. The underlying assumptions of the model are, therefore, successively or incrementally reachable categories of the variable $Y_i \in \{i = 1, \dots, d\}$ (Hausman and McFadden, 1984; Wong and Mason, 1985; Tutz, 2005).

The accessibility of the category is stepwise and explicitly modeled by a sequence of dichotomous transitions. The results describe the influence of independent variables on the conditional chance of the transition to a certain category compared to the conditional chance of remaining in its most recent category (Wong and Mason, 1985; Tutz, 2005). Due to the non-linear model, the estimated coefficients cannot be interpreted as marginal effects. In order to obtain the marginal effects of the independent variables on the conditional chance of the transition to another category, the 'odds ratio' needs to be defined. This is the ratio of the odds of an event occurring in one group to the odds of it occurring in another group[4]. The term is also used to refer to sample-based estimates of this ratio.

For our application of the SLM, the following transitions of the CRI are considered:

1. The conditional chance of the transition from the category of loans, for which all installments are paid on time (Y_i = 1), to the category of loans for which at least one installment payment is at least one day past the due date ((Y_i = 2) + (Y_i = 3) + (Y_i = 4)).
2. The conditional chance of the transition from the category of loans for which at least one installment payment is past the due date of at maximum 29 days (Y_i = 2), to the category of loans for which at least one installment payment is at least 30 days past the due date ((Y_i = 3) + (Y_i = 4)).
3. The conditional chance of the transition from the category of loans for which at least one installment payment is past the due date of at maximum 89 days (Y_i = 3), to the category of loans for which at least one installment payment is at least 90 days past the due date (Y_i = 4).

The process starts in $Y_i = 1$; hence, in the present application, it starts in the category of credits for which all installment payments are paid on time. The probability of transition regarding $Y_i > 1$ is modeled using a binary model:

$$P\ (Y_i = 1|x_i) = F\ (\beta_{01} + \boldsymbol{x'_i}\,\boldsymbol{\beta}) \tag{4}$$

with the logistic function F and $x'_i\,\beta$ as a linear predictor. 01 stands for the first category. The r-th step is generally determined by:

$$P\ (Y_i = r|Y_i\ \geq r, x_i) = F\ (\beta_{0r} + \boldsymbol{x'_i}\,\boldsymbol{\beta}). \tag{5}$$

The process stops as soon as the transition is not performed. The overall model is obtained by:

$$P\ (Y_i = r|Y_i\ \geq r, x_i) = F\ (\beta_{0r} + \boldsymbol{x'_i}\,\boldsymbol{\beta}), \qquad r = 1,\ldots,q \tag{6}$$

with $q = d - 1$.

Due to the conditional chances of the transition between the categories, the sequential logit model can be illustrated as follows:

$$\log \frac{P\ (Y_i = r|Y_i \geq r, x_i)}{1 - P\ (Y_i = r|Y_i \geq r, x_i)} = \beta_{01} + \boldsymbol{x'_i \beta}. \tag{7}$$

In our application, the linear predictor $\boldsymbol{x'_i}\,\boldsymbol{\beta}$ stands for:

$$\boldsymbol{x'_i}\,\boldsymbol{\beta} = \beta_0 + \beta_1 \cdot\ I_t^{ac} + \boldsymbol{\beta_2} \cdot \boldsymbol{c_{i,t}} + \boldsymbol{\beta_3} \cdot \boldsymbol{s_{i,t}} + \boldsymbol{\beta_4} \cdot \boldsymbol{a_t} + \boldsymbol{\beta_5} \cdot \boldsymbol{b_i} + \boldsymbol{\beta_6} \cdot \boldsymbol{w_i} + v.$$

(8)

[4] A coefficient equal to 0 results in an odds-ratio of 1 (no difference in the odds). A coefficient higher than 0 results in an odds-ratio >1 (the odds of the first group are larger). A coefficient lower than 0 results in an odds-ratio <1 (the odds of the first group are smaller).

In equation (8), $c_{i,t}$ is a vector describing the loan characteristics. The loan attributes include the loan volume and dichotomous (1/0) variables, indicating whether or not the borrower provided collateral, received a grace period, or received a repeat loan. $s_{j,t}$ is a vector for the socio-demographic characteristics of the clients, including age, gender, number of family members and work experience of the borrower. a_t is a vector of dummy variables for the year in which the application for the credit was made. b_i is a vector of dummy variables that represents the 16 different branch offices of the ABM. w_i is a vector of dummy variables testing for the influence of the weather station at which the weather variable is measured.

5. Results

5.1 Descriptive statistics

The descriptive statistics in Table 2 show the means for the dependent and the independent variables, as well as their minimum, maximum, and standard deviation for all loans in our dataset.

[Insert Table 2 here]

Table 2 shows that the installment payments of 33% of all loans disbursed by the ABM to small-scale farmers were paid on time, at least one installment payment was at least one day overdue for 55% of all loans, at least one installment payment was at least 30 days overdue for 7% of all loans, and at least one installment payment was at least 90 days overdue for 5% of all loans. Accumulated precipitation sums are measured between 72.50mm (Antananarivo, March 2007) and 610mm (Antananarivo, March 2011). The average loan volume is about 1.2 million MGA, which corresponds to nearly half of the average asset value of the farms in the area of investigation (2.43 million MGA) (Accès Banque Madagascar, 2013). For 87% of the loans disbursed, borrowers pledged collateral to the MFI. Since borrowers were often unable to pledge collateral with a high economic value, items with a high emotional value for the borrower, such as an owned bicycle or television, were pledged. Almost half of the credit borrowers were female. In principle, the credit borrower is also the decision maker. However, as all of the farms in our dataset are family businesses, decisions are often made jointly. In some cases, women may work in the field while males have off-farm labor. Therefore, household incomes maybe composed of both agricultural income and non-agricultural income. Nevertheless, the share of agricultural income is always more than 50% (Accès Banque Madagascar, 2013). Off-farm labor mostly consists of rice transportation to the harbor (upstream area of agriculture), rice breeding / propagation (downstream area of agriculture) or tourism. Consequently, in most cases, the non-agricultural income sources are also highly weather-related.

5.2 Estimation results of the linear probability models

Table 3 shows the estimation results for the repayment performance of loans granted to small-scale farmers by ABM using the LPM. We estimate the effect of rainfall on the repayment performance (CRI-1, CRI-30, CRI-90) for the accumulated precipitation in February, March and April, respectively. Therefore, we estimate nine separate LPMs. The variables concerning the credit attributes and the socio-demographic characteristics are the same for all estimations. The first column depicts the effect of the accumulated precipitation in February on the repayment performance of loans granted to small-scale farmers. The second and third columns show the estimation results for the effect of the accumulated precipitation for March and April, respectively.

[Insert Table 3 here]

The results suggest that an excessive amount of rain in the harvest period reduces the repayment performance of loans granted to small-scale farmers in Madagascar. For CRI-1, the effects of the accumulated precipitation from February, March, and April, respectively, are significant at a significance level of 99%. Furthermore, the accumulated precipitation from March and April are significant for CRI-30 and CRI-90 at a significance level of 90%. Moreover, results show that the quadratic terms of precipitation significantly affect credit risk in agricultural microfinance. Therefore, increasing precipitation has a decreasing effect on credit risk.

Additionally, the results suggest that loan characteristics affect the repayment performance as well, e.g., collateral positively affects the repayment performance in every case. Loans with grace periods and repeat clients further increase the probability that at least one installment payment is at least one day overdue. Concerning the socio-demographic characteristics, the LPM finds an effect of the age, the gender and the work experience of a borrower on the repayment performance.

5.3 Estimation results of the sequential logit model

As the LPM cannot take into account the gradual accessibility of the different default levels, we estimate an SLM for the month for which the LPM reveals the highest effect of excessive rain on the repayment performance and compare the results to those from the LPM. The results from the LPM show that, on average, the precipitation in March has the highest influence on the credit risk indicators. Thus, the aggregated precipitation of March is used for the SLM estimation.

Table 4 shows the repayment performance of loans granted to small-scale farmers by the ABM, based on the SLM.

[Insert Table 4 here]

Results show that an increasing amount of precipitation in March during the harvesting period for rice in the highland of Madagascar increases the conditional chance that at least one installment payment of a loan is at least one day past the due date (CRI-1). The conditional chance that at least one installment payment of a loan is at least 30 or 90 days past the due date (CRI-30/CRI-90) also increases with each additional millimeter of precipitation in March. Thereby, the SLM (and the LPM) prove a significant influence of the accumulated precipitation sum from March on the performance of loans granted to small-scale farmers in Madagascar. Thus, hypothesis 1 is confirmed. If it rains roughly 610mm, as was the case in March 2011, the conditional chance for CRI-1 is about 35 times higher than the chance given an average amount of rain (380mm). In comparison to the average amount of precipitation, the conditional chance for CRI-90 doubles with a precipitation amount of 425mm.

We obtain a significant impact for the examined loan attribute 'loan volume' on the probability that at least one installment payment is in arrears by at least 30 days. If a borrower pledges collateral, the conditional chance that at least one installment payment of a loan is at least 1, 30 or 90 day(s) past the due date decreases by about 92%, 97% and 73%, respectively. This value seems to be quite high in relation to the relative marginal effects of other variables. However, it needs to be considered that this refers to a dummy variable, meaning that this is a (non-repeatable) single effect. Furthermore, 'grace periods' significantly increase the conditional chance that at least one installment payment is in arrears by at least one day. Accordingly, the adaptation of standardized microloans to the particularities of the agricultural sector seems to increase the credit risk for the MFI. Furthermore, we find that being a 'repeat client' reduces the repayment performance significantly for CRI-1 and CRI-30. Lending to the same client again increases the conditional chance that at least one installment payment of a loan is at least 30 days past the due date by about 84%.

Similar to the LPM, the SLM finds a significant influence for age, gender and the work experience of a borrower on the repayment performance, while 'number of family members' does not significantly affect the repayment performance. In difference to other studies (Godequin, 2004; Roslan and Karim, 2009; Armendáriz de Aghion and Morduch, 2010) our results show that women are less reliable and repay their installment payments more unpunctually. Compared to a credit disbursed to a man, the conditional chance that at least one installment payment of a loan is at least 1 or 30 day(s) past the due date increases by 17% and 78%, respectively, if a loan is granted to a woman. Thus, hypothesis 2 which states that loan attributes and socio-demographic characteristics affect the performance of loans granted to small-scale farmers in Madagascar, can also be confirmed.

Comparing the effects of excessive rainfall in March on the repayment performance of loans granted to small-scale farmers estimated by the LPM and the SLM yields very similar results for most variables with both models. First, the effect of excessive rain in March on the conditional chance that at least one installment payment is at least 90 days overdue is significant at the 90% level when estimating with the help of an LPM and significant at the 95% level based on estimations of the SLM. Furthermore, the effects for repeat loans and gender of the borrower on the conditional chance that at least one installment payment of a loan is at least 30 days past the due date is significant at the 90% level when estimated with an SLM but not significant when estimating by an LPM.

6. Conclusions

Although microfinance in developing countries has made rapid progress in recent years, small-scale farmers in rural areas are still undersupplied with capital. It is frequently stated in the literature that this is primarily caused by weather risks. These risks affect the profitability of agricultural production and increase the cash flow volatility. This can also affect the ability of farmers to pay loan installments on time. We estimate the effect of weather events on the repayment performance of loans granted to small-scale farmers in Madagascar by combining original data from a Madagascan MFI with weather data from three different local weather stations. The analysis is achieved using a two-step estimation approach based on linear probability models and a sequential logit model.

The results reveal that an excessive amount of precipitation in the harvesting period of rice increases the credit risk of loans granted to small-scale farmers in Madagascar. Since the returns from weather index-based insurance (at least as a future contract) are perfectly correlated with weather events (Turvey, 2001; Vedenov and Barnett, 2004), we can set the effect of weather events on the repayment performance of loans equal to the effect of the returns of weather index-based insurance on the repayment performance of loans. Thus, our results imply that weather index-based insurance might have the potential to mitigate a certain part of the risk in agricultural lending.

Furthermore, the results confirm that credit features affect the repayment performance of loans. More specifically, we found that repeated lending increases the credit risk of loans granted to small-scale farmers. Consequently, the ABM seems to notably have a problem with motivating their 'repeat clients' to pay their installments without any arrears.

However, our results cannot be generalized. It has to be taken into account that only the small-scale farmers who applied for and obtained a loan are recorded. Small-scale farmers, who did not request credit (due to e.g. high transaction costs, geographical distance between bank and client, a lack of financial knowledge, or mistrust towards banks), are not included in our data. Conjointly, the farmers that applied for and did not obtain a loan are not included in our data. Those farms were refused because the ABM expected them to be more risky than other agricultural clients, whose farms may have a lower weather risk exposition (e.g., the farm is situated on a hillside). Moreover, apart from variables regarding loan features and socio-demographic characteristics, further studies should also take into account intensity-related variables, such as the use of fertilizer. Unfortunately, our data set does not include any information about these variables.

Since this is one of the first studies that empirically investigates the relationship between weather risks in agricultural production and credit risk in agricultural lending, there is a considerable need for further research. The latter should then concentrate on the development of index-based insurances in agricultural lending and consider interventions on different levels, e.g., insurance on the farm and the bank level. The determined influence of excessive precipitation in the harvest season on the repayment performance of loans granted to small-scale farmers is not necessarily transferable to other types of production and other regions. Regional characteristics of agriculture in different countries, as well as cultural influences, may have different effects on the credit risk.

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Table 1: Correlation matrix of precipitation sums and temperature sums measured at the three weather stations of Antananarivo (Ivato), Antsirabé, Tamatave (Toamasina)

	Antananarivo (Ivato)		**Antsirabé**		**Tamatave (Toamasina)**	
	Precipitation [a)]	**Temperature [b)]**	**Precipitation [a)]**	**Temperature [b)]**	**Precipitation [a)]**	**Temperature [b)]**
Antananarivo (Ivato)	1	1				
Antsirabé	0.78	0.99	1	1		
Tamatave (Toamasina)	0.69	0.97	0.76	0.99	1	1

a) Precipitation sums measured in March.
b) Temperature sums measured in October.

Table 2: Descriptive statistics for loans the ABM granted to small-scale farmers (n = 3,534)

Variable	Unit	Mean	SD	MIN	MAX
Dependent variables					
CRI-0	1/0 [a)]	0.33	-	-	-
CRI-1	1/0 [a)]	0.55	-	-	-
CRI-30	1/0 [a)]	0.07	-	-	-
CRI-90	1/0 [a)]	0.05	-	-	-
Independent variables					
Accumulated February precipitation					
Antananarivo (Ivato)	millimeters	215.21	137.06	80.09	407.60
Antsirabé	millimeters	294.36	143.96	112.54	510.23
Tamatave (Toamasina)	millimeters	265.87	189.85	126.85	493.65
Accumulated March precipitation					
Antananarivo (Ivato)	millimeters	379.46	198.24	72.50	610.12
Antsirabé	millimeters	369.33	175.55	166.76	590.32
Tamatave (Toamasina)	millimeters	257.50	152.63	146.76	464.32
Accumulated April precipitation					
Antananarivo (Ivato)	millimeters	174.13	112.63	85.07	275.61
Antsirabé	millimeters	225.92	141.69	112.63	336.78
Tamatave (Toamasina)	millimeters	186.84	145.73	97.45	412.79
Loan characteristics					
Loan volume	ths.MGA [b)]	1,188.52	1,509.63	100.00	20,000.00
Loan collateral	1/0 [a)]	0.87	-	-	-
Grace period	1/0 [a)]	0.36	-	-	-
Repeat client	1/0 [a)]	0.30	-	-	-
Socio-demographic characteristics					
Age	years	40.55	9.79	20.00	77.00
Gender (female)	1/0 [a)]	0.46	-	-	-
Family members	number	5.05	1.90	1	17
Work experience	month	162.26	152.17	1	723

a) Dummy variable: 1= yes, 0 = no. Mean values for dummy variables (1/0) indicate ratios.
b) Ths.MGA = Thousand Madagascar Ariary.

Table 3: Estimation results of linear probability regressions for loan repayment (n = 3,534) [a)]

Variable	Unit	Coefficient		
		February precipitation	March precipitation	April precipitation
CRI-1		**$R^2 = 0.46$**	**$R^2 = 0.52$**	**$R^2 = 0.48$**
Precipitation	millimeters	0.000259***	0.00233***	0.000758***
Precipitation square	millimeters	-5.40e-07***	-2.43e-06***	4.27e-06***
Loan volume	ths.MGA[b)]	5.51e-06	2.21e-06	3.62e-07
Loan collateral	1/0 [c)]	-0.13***	-0.16***	-0.15***
Grace period	1/0 [c)]	0.14**	0.12**	0.15**
Repeat client	1/0 [c)]	0.10***	0.52***	0.12***
Age	years	0.00669*	0.06*	0.00675*
Age square	years	-0.000107**	-0.000069**	-0.000104**
Gender (female)	1/0 [c)]	0.03*	0.03*	0.04**
Family members	number	-0.02	-0.02	-0.02
Work experience	month	-0.000329***	-0.00026**	0.000296***
Work experience square	month	-2.17e-07***	1.87e-07**	1.94e-07***
CRI-30		**$R^2 = 0.12$**	**$R^2 = 0.26$**	**$R^2 = 0.26$**
Precipitation	millimeters	0.0000867	0.00930*	0.000427*
Precipitation square	millimeters	-1.91e-07	-2.35e-06*	-2.21e-06*
Loan volume	ths.MGA [b)]	-1.68e-05	-1.62e-05**	-1.68e-05**
Loan collateral	1/0 [c)]	-0.05***	-0.05***	-0.05***
Grace period	1/0 [c]	-0.01	-0.01	-0.01
Repeat client	1/0 [c)]	0.00635	0.00544	0.00614
Age	years	0.00162	0.00153	0.00137
Age square	years	-0.0000203	-0.00001	-0.000021
Gender (female)	1/0 [c)]	0.00608	0.00503	0.00581
Family members	number	-0.00181	-0.00164	-0.00184
Work experience	month	-0.0000273	-0.0000208*	-0.000062
Work experience square	month	7.71e-08	1.33e-08*	4.60e-08
CRI-90		**$R^2 = 0.09$**	**$R^2 = 0.26$**	**$R^2 = 0.25$**
Precipitation	millimeters	0.0000321	0.000165*	0.000337*
Precipitation square	millimeters	-6.83e-08	-3.19e-06*	-1.53e-06*
Loan volume	ths.MGA[b)]	-8.28e-06	-8.08e-06	-8.26e-06
Loan collateral	1/0 [c)]	-0.02***	-0.02***	-0.02***
Grace period	1/0 [c)]	-0.00478	-0.00377	-0.00437
Repeat client	1/0 [c)]	0.00714	0.00733	0.00675
Age	years	0.000795	0.000697	0.000822
Age square	years	-0-0000105	-9.54e-06	-0.0000109
Gender (female)	1/0 [c)]	-0.00212	-0.00201	-0.00265
Family members	number	-0.00265	-0.00247	-0.00273
Work experience	month	-6.12e-07	-5.53e-06	-1.29e-07
Work experience square	month	1.71e-09	1.06e-09	2.12e-09

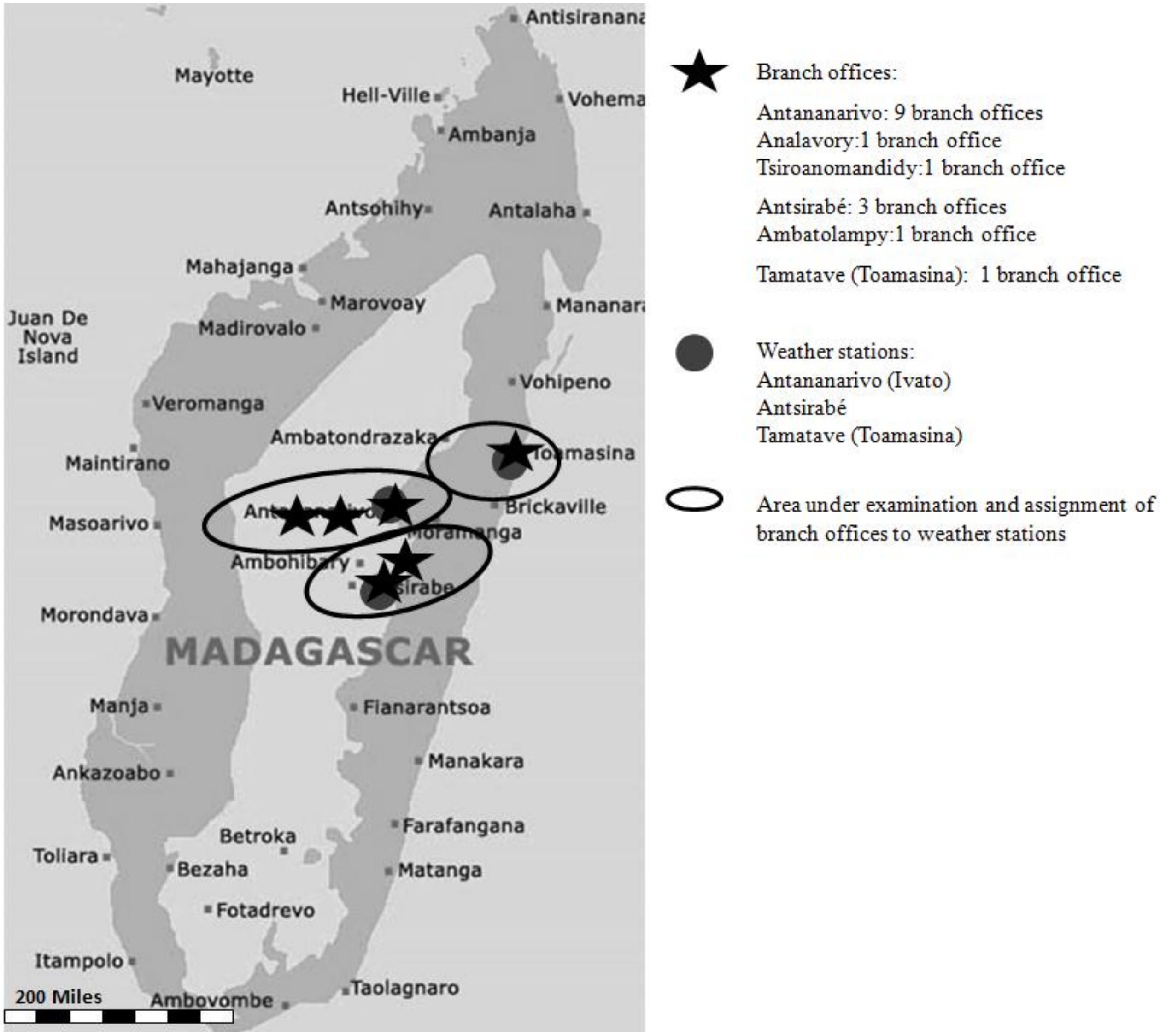
a) To correct our results from the influence of those variables, we checked the influences of the year and the branch of lending. The results are not shown in Table 2. ***,**, and * describe a significance level of 99%, 95%, and 90%, respectively. Robust standard errors are clustered at the weather station level.
b) Ths.MGA = Thousand Madagascar Ariary.
c) Dummy variable: 1= yes, 0 = no.

Table 4: Estimation results of the sequential logit model for loan repayment (n = 3,534) [a)]

Variable	Unit	Coefficient	Odds ratio	Relative marginal effect
(CRI-1 + CRI-30+ CRI-90) versus CRI-0				
March precipitation	millimeters	0.0136*** (0.000253)	1.0136	1.36%
March precipitation square	millimeters	-0.0000141*** (0.00000403)	1.0000	-0.01%
Loan volume	ths.MGA [b)]	0.18e-05 (0.000132)	1.0000	0.01%
Loan collateral	1/0 [c)]	-0.65*** (0.14)	0.5220	-91.55%
Grace period	1/0 [c)]	0.61** (0.25)	1.8404	84.04%
Repeat client	1/0 [c)]	0.52*** (0.09)	1.6820	68.20%
Age	years	-0.03762* (0.0002431)	0.9631	-3,83%
Age square	years	0.000598** (0.000172)	1.0006	0.06%
Gender (female)	1/0 [c)]	0.16* (0.09)	1.1735	17.35%
Family members	number	-0.09 (0.09)	0.9139	-9.41%
Work experience	month	-0.0013*** (0.00049)	0.9870	- 0.13%
Work experience square	month	9.20e-07** (3.68e-07)	1.0000	0.01%
(CRI-30 + CRI-90) versus CRI-1				
March precipitation	millimeters	0.0218* (0.0116)	1.0220	2.20%
March precipitation square	millimeters	-0.0000236* (0.0000135)	1.0000	-0.01%
Loan volume	ths.MGA [b)]	0.00120** (0.000526)	1.0012	0.12%
Loan collateral	1/0 [c)]	-0.68*** (0.37)	0.5066	-97.38%
Grace period	1/0 [c)]	0.55 (0.35)	1.7333	76.03%
Repeat client	1/0 [c)]	0.61* (0.37)	1.8404	84.04%
Age	years	-0.02130 (0.137933)	0.8177	-2.03%
Age square	years	0.0027169 (0.001655)	1.0027	0.27%
Gender (female)	1/0 [c)]	0.58* (0.33)	1.7860	78.60%
Family members	number	-0.15 (0.30)	0.8607	-16.18%
Work experience	month	-0.0041* (0.00262)	0.9959	-0.41%
Work experience square	month	2.34e-06* (1.92e-06)	1.0000	0.01%
CRI-90 versus CRI-30				
March precipitation	millimeters	0.00778** (0.001.64)	1.0078	0.78%
March precipitation square	millimeters	-0.0000742* (0.0000352)	1.0000	-0.01%
Loan volume	ths.MGA [b)]	-0.00179 (0.000902)	0.9982	-0.18%
Loan collateral	1/0 [c)]	-0.55*** (0.51)	0.5769	-73.33%
Grace period	1/0 [c)]	-0.62 (0.36)	0.5379	-85.89%
Repeat client	1/0 [c)]	0.56 (0.32)	1.7507	75.07%
Age	years	-0.16 (0.13)	1.0942	-17.35%
Age square	years	0.00239 (0.0017)	0.9997	0.24%
Gender (female)	1/0 [c)]	0.03 (0.46)	1.0305	3.05%
Family members	number	-0.21 (0.44)	0.8106	-23.37%
Work experience	month	-0.019* (0.012)	0.9812	1.92%
Work experience square	month	0.0000803* (0.0000476)	1.0001	-0.008%
Likelihood-Ratio-Test $\chi^2(58)$		469 (p-Wert < 0.001)		
Prob. > chi2		<0.001		

a) To correct our results from the influence of those variables, we checked the influences of the year, branch of lending, and the weather station, where the March precipitation was measured. The results are not shown in Table 3. ***,**, and * describe a significance level of 99%, 95% and 90%, respectively. Standard errors in parentheses.
b) Ths.MGA = Thousand Madagascar Ariary.
c) Dummy variable: 1= yes, 0 = no.

Figure 1: Location of the branch offices and weather stations under examination



Source: http://www.worldguide.html (modified)