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The Effect of Rainfall Changes on Microcredit Demand in Rural Morocco

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Abstract

In this study, we aim to address two key questions: First, is there a relationship between past rainfall amounts in specific communes and microcredit demand within those communes? Second, if such a relationship exists, how do rainfall shocks impact microcredit demand? Our analysis, using a panel data random effects model, revealed a statistically significant positive correlation between previous rainfall amounts and the number of loans taken in rural communes, with significance at the 0.01 confidence level. We investigated the impact of positive and negative rainfall shocks on microcredit demand. To do so, we divided our sample into two categories: those affected by positive rainfall shocks and those affected by negative rainfall shocks for each duration. We consistently observed a positive relationship in the subsample affected by only positive rainfall shocks. However, in the subsample experiencing only negative rainfall shocks, the sign of coefficients changed. We can infer that microcredit demand does not immediately increase during the early days of a negative rainfall shock. Instead, demand begins to rise as the severity of the shock intensifies.

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Introduction

Microcredit, a financial service that offers small loans to low-income individuals, has become increasingly prominent as a tool for poverty alleviation and economic empowerment. Many impoverished people are excluded from the formal financial system due to their inability to provide physical collateral. This situation is exacerbated in rural areas where access to formal banking services remains limited.

Although microcredit has a long history, modern microfinance was founded by Bangladeshi professor Muhammad Yunus at Chittagong University in Bangladesh. In the early 1970s, Bangladesh experienced civil war, genocide, and famine, resulting in a significant increase in poverty levels. Muhammad Yunus observed that a woman in a nearby village earned only 2 cents per day as profit. Despite this meager income, she still had to borrow money from local money lenders at high interest rates to purchase raw materials. In 1976, Yunus lent interest-free $27 to forty-two women, breaking their vicious cycles. His goodwill initiative evolved into an institution, leading to the establishment of Grameen Bank in Bangladesh in 1983. By 1998, Grameen Bank clones had been introduced in fifty-eight countries, with a total lending amount of $2.3 billion to 2.3 million families (Yunus, 2007). The United Nations designated 2005 as the International Year of Microcredit, and Professor Yunus and Grameen Bank were honored with the Nobel Peace Prize in 2006. As of January 2023, Grameen Bank has nearly 10.3 million borrowers, with 96.85% of them being women in Bangladesh (Grameen Bank, 2023).

The success of microfinance programs in developing countries has captured the attention of both academics and policymakers worldwide. Extensive literature now analyses various aspects of microcredit programs, which can be broadly categorized into two areas: theoretical analysis of distinctive features in microcredit contracts, such as joint liability, and empirical evaluations of program effectiveness (Shahe Emran et al., 2021; Banerjee, 2013). However, consensus remains elusive in these areas. For instance, Crepon et al. (2015) discovered that borrowers' livestock size increased in Rural Morocco after using microcredits. In contrast, Zhang et al. (2018) found that the number of herds may decrease in Inner Mongolia, China. The reason behind this discrepancy lies in the fact that during poor years, borrowers used loans to purchase winter forage. Despite this, borrowers ultimately sold more livestock due to the repayment structure of the standard one-year loan term.

The demand side of microcredit remains underdeveloped. A common assumption is that poor individuals, if given the opportunity, would readily access microcredits. For instance, in 2007, it was estimated that the total number of microcredit borrowers reached approximately 100 million. Considering that there are 3 billion poor people globally, around half of them (1.5 billion) could potentially qualify for microcredits. In other words, the demand for microcredit far exceeds its supply (Standard & Poor's, 2007). However, Anand and Rosenberg (2008) argue that many researchers tend to overestimate this demand. The sheer number of poor people can be misleading. Some individuals simply do not want microloans, while others may not qualify for credit. Additionally, borrowing behavior varies—some may not borrow consistently.

Pariente (2011) found that 58% of agricultural households in rural Serbia are uninterested in any loans currently available in the market. Similarly, Crepon et al. (2015) demonstrated that even in an environment with limited credit access, the average take-up of microfinance is only 13% in the general population and 17% in their designated higher probability sample in rural Morocco. Surprisingly, half of the clients did not seek any other credit the following year. This study underscores the challenge of predicting microcredit utilization, even when considering a rich set of baseline characteristics for potential borrowers.

Scholars worldwide have extensively studied the factors influencing microcredit participation. Cheng (2007) discovered that demand for microcredit is positively correlated with family income, off-farm investment opportunities, and the educational level of female borrowers in China. Mohamed (2008) explored socioeconomic features among Zanzibar farmers, including the number of bank accounts in a household, the value of productive assets, income levels, livestock ownership, and previous formal credit history—all of which impact microcredit participation. Pariente (2011) evaluated financial demand in rural Serbia, revealing that farmers' wealth, farm size, household size, and credit experience contribute to credit demand, while age diminishes it. Additionally, interest rates, loan sizes, and the presence of a grace period affect credit demand. Li et al. (2011) examined key factors influencing microcredit accessibility for rural households in China. They found that demand-side factors such as household size, educational level, distance, income, asset value, savings, official status in the village, and attitude toward debt, along with supply-side factors like interest rates, document requirements, and loan processing time, influence households' likelihood of accessing microcredit. Qin et al. (2019) identified factors such as village leadership, crop production costs, loan size, family income, and village head as a loan guarantor that increase microcredit utilization.

Morvant-Roux et al. (2014) analyzed the same dataset that Crepon et al. (2015) used in their study to explore why microcredit demand in rural areas was low and varied. They highlighted two key factors influencing participation and default behavior in microcredit programs: agroecological conditions (such as distance from urban areas) and social norms related to debt perception. Their research revealed interesting patterns. In regions where people view microcredit as originating from the King, there are fears of potential sanctions, leading to lower participation and higher default rates. Conversely, in areas where microcredit is perceived as state-sponsored, borrowers may treat it as nonrepayable debt, resulting in widespread participation and default.

As mentioned earlier, predicting who will use microcredit is challenging. However, understanding when poor individuals seek microcredit presents an even more complex question. While existing literature has explored various determinants of microcredit demand, such as household characteristics and microcredit features, the specific role of climate factors remains largely unexplored.

To the best of our knowledge, the study by Abay et al. (2021) investigates the impact of rainfall uncertainty on credit uptake among rural farm households in Ethiopia. Their primary data source is the LSMS-ISA surveys, a collaborative project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank. These surveys span three rounds conducted in 2011/12, 2013/14, and 2015/16, covering various topics related to agricultural production. Abay et al. rely on rainfall data derived from the POWER (Prediction of Worldwide Energy Resource) Data Archive by NASA. These daily spatial time-series data are available globally at a 55x55 km grid spatial resolution, collected exclusively through satellite observations. The study's dependent variable is households' uptake of credit from formal sources. It is a binary indicator, assuming a value of 1 for households that accessed credit from formal sources in the last 12 months and 0 otherwise. The most critical explanatory variables in their analysis include the coefficient of variation of inter-annual total rainfall, constructed based on data from the ten years preceding each survey period, as well as the total rainfall of the prior year. Abay et al. find that both rainfall variability and total rainfall from the previous year discourage the uptake of agricultural credit.

In this study, we aim to address two key questions: First, is there a relationship between past rainfall amounts in specific communes and microcredit demand within those communes? Second, if such a relationship exists, how do rainfall shocks impact microcredit demand?

Microcredit has been present in Morocco since the mid-1990s, and the country is often regarded as a flagship for Arabic microcredit initiatives (Morvant-Roux et al., 2014). As of 2021, approximately 87% of the country's crop production relies heavily on rainfed agriculture, making it highly susceptible to variations in rainfall. The agricultural sector, including livestock, contributes around 15% to Morocco's GDP and 23% to its exports. Moreover, this sector accounts for 69% of rural employment (World Bank Group, 2021). Given these factors, Morocco provides an ideal context for investigating the relationship between rainfall and microcredit demand.

To explore this, we obtained an extensive microcredit dataset from Al Amana, the largest microfinance institution in Morocco. Additionally, we acquired highly accurate rainfall data from the CGMS-Maroc (Crop Growth Monitoring System). Calculating the number of loans taken in each rural commune per month, we combined this information with additional explanatory variables from The High Commission for Planning, which serves as the primary producer of official statistics in Morocco. Our analysis, using a panel data random effects model, revealed a statistically significant positive correlation between previous rainfall amounts and the number of loans taken in rural communes, with significance at the 0.01 confidence level.

In our study, we investigated the impact of positive and negative rainfall shocks on microcredit demand. To do so, we divided our sample into two categories: those affected by positive rainfall shocks and those affected by negative rainfall shocks for each duration.

Remarkably, we consistently observed a positive relationship in the subsample affected by only positive rainfall shocks. However, in the subsample experiencing only negative rainfall shocks, the sign of coefficients changed. Specifically, for short-duration variables, the sign changes occurred around the p50 percentile. As the time duration increased, the percentile at which the coefficient sign changed decreased.

From these findings, we can infer that microcredit demand does not immediately increase during the early days of a negative rainfall shock. Instead, demand begins to rise as the severity of the shock intensifies.

Data

Al Amana, a non-profit organization, holds a prominent position in the microfinance sector. As of March 2024, it boasts 646 agencies, employs over 2400 workers, and manages more than 280,000 active loans in Morocco (Al Amana, 2024). Al Amana generously shared a comprehensive dataset containing details of all loans disbursed by its rural branches between January 2018 and December 2023.

This dataset contains essential details for each of the 307,000 individual loans, including the contract number, loan amount, actual release date, and the rural commune associated with the bank branch. Notably, our dataset covers 187 rural communes across Morocco.

Figure 1 illustrates the total number of loans disbursed each year. We observe a significant decline in loan numbers annually. The pandemic in 2020 likely contributed to this decrease, although loan volumes did not fully recover afterward.

Figure 2 provides a monthly breakdown of loan counts. The pandemic impact is evident, with loan numbers dropping between March 2020 and June 2020. However, demand rebounded in July 2020, compensating for the previous decline. We excluded these five pandemic-affected months from our sample. Overall, the trend remains downward.

Figure 3 depicts the total value of loans per year. While the total loan value significantly decreased in 2020, it did not return to pre-pandemic levels. Considering positive inflation, the real value of loans declined even more sharply.

Figure 4 focuses on the monthly loan values. Although subtle, a slight downward trend is discernible.

Additionally, we calculated the monthly loan count for each rural commune from 2018 to 2023. For instance, Al Amana disbursed 17 loans in Aquermoud, but a substantial 61 loans in Sidi Bibi in January 2018. As expected, loan volumes correlate with the population of each locality. We derived population figures for the communes from the last population census conducted in September 2014 in Morocco.

Figure 1: Total Number of Loans for Each Year

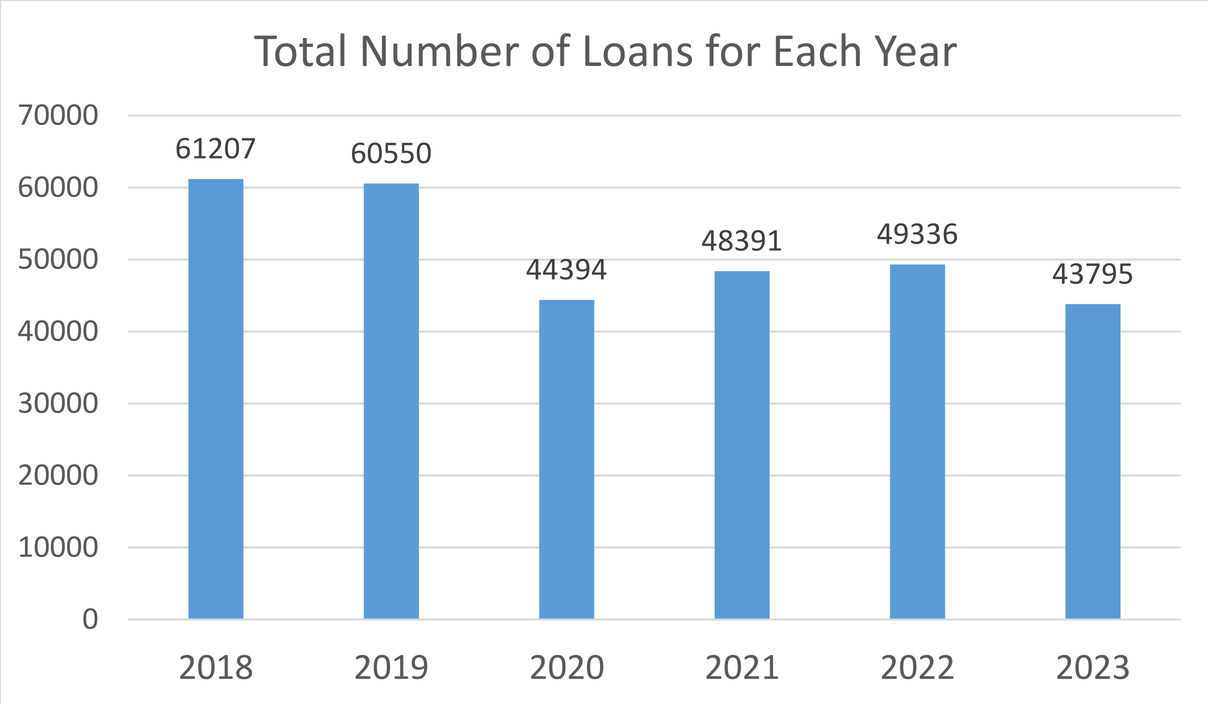


Figure 2: Total Number of Loans for Each Month

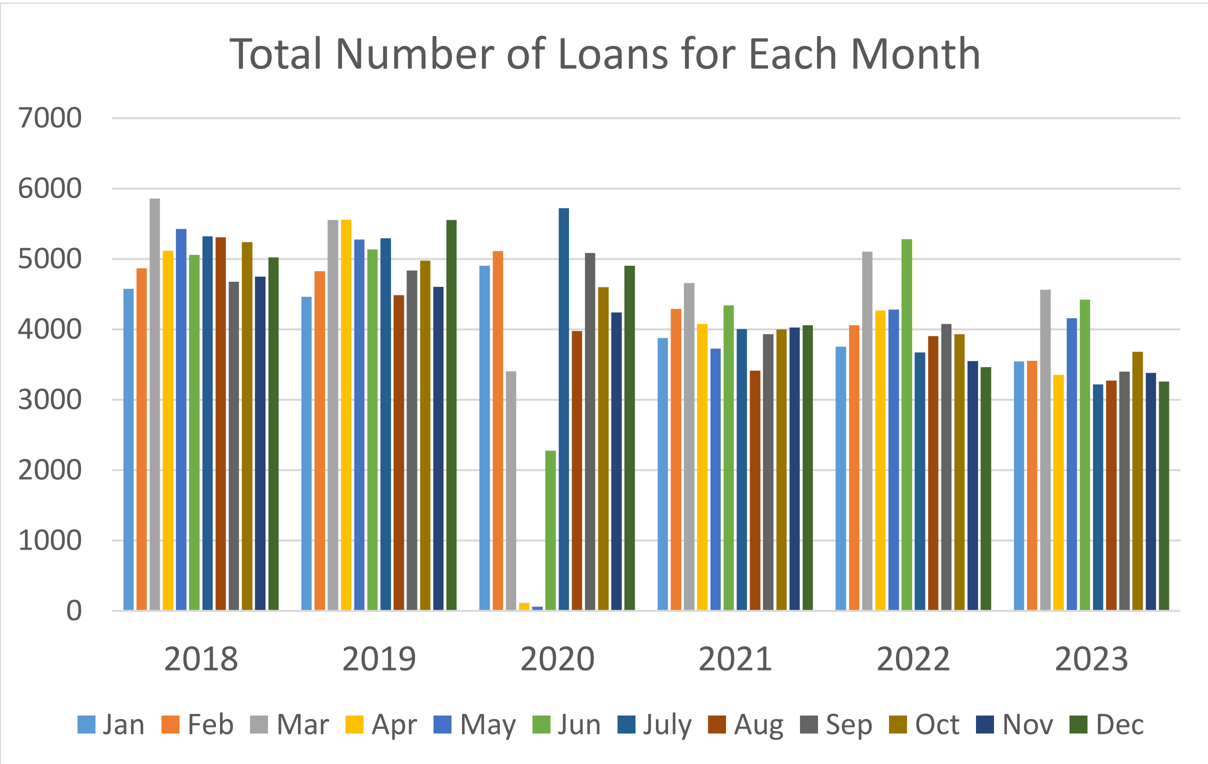


Figure 3: Total Value of Loans for Each Year

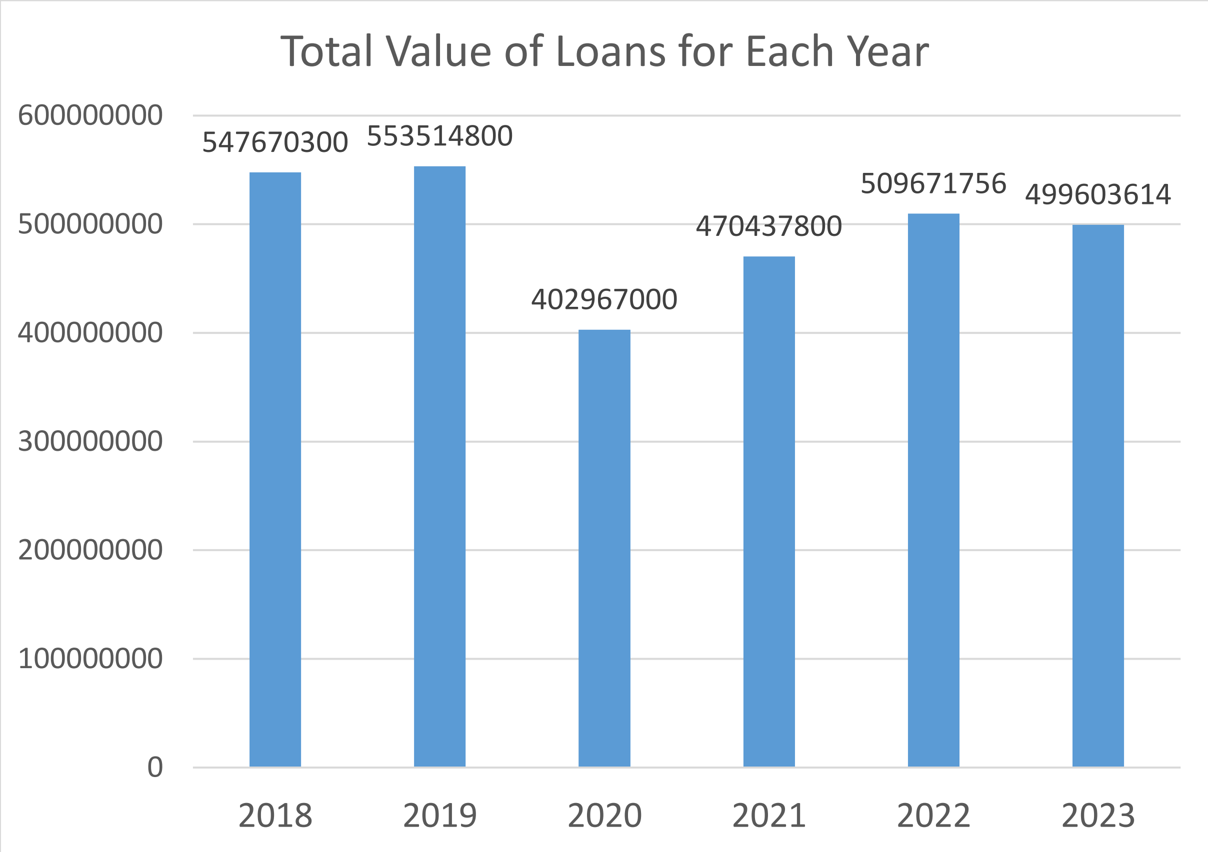
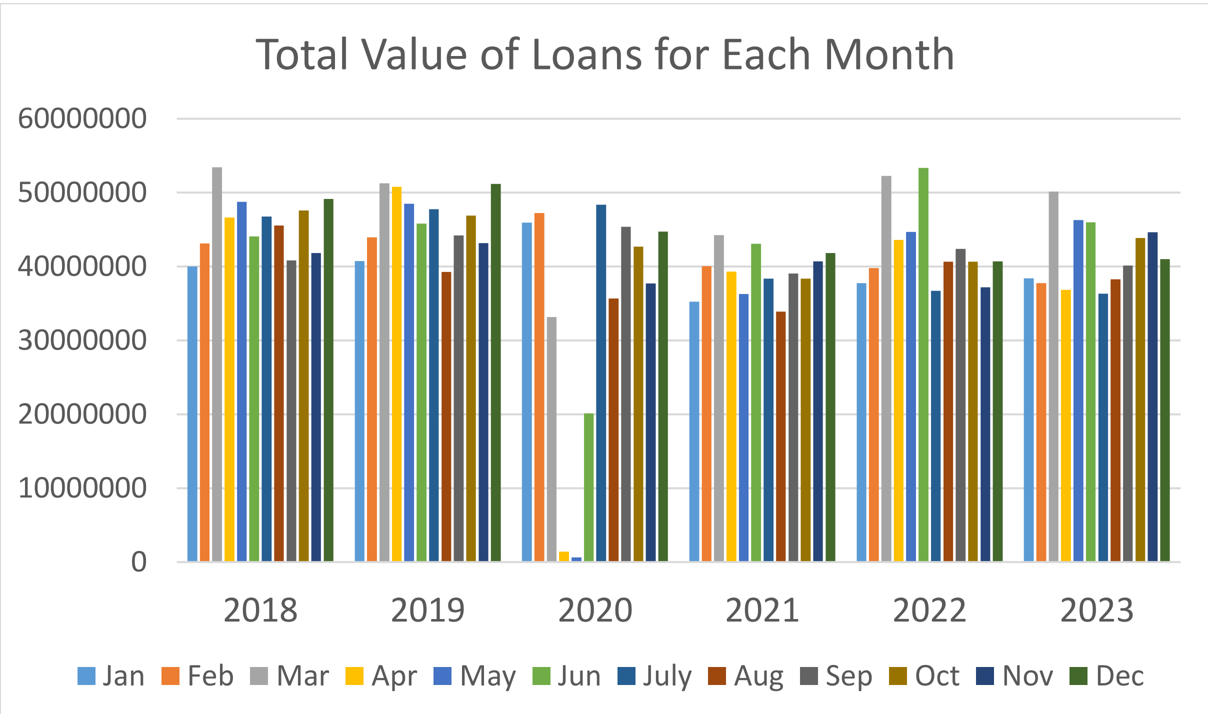


Figure 4: Total Value of Loans for Each Month



The CGMS-Maroc (Crop Growth Monitoring System) is a national agrometeorological monitoring system in Morocco. It emerged from a strategic collaboration among various national institutions, including the National Institute for Agronomic Research (INRA), the General Directorate of Meteorology (GDM), the Ministry of Agriculture (Directorate of Strategy and Statistics), and the Agronomic and Veterinary Institute (IAV) Hassan II of Morocco. Additionally, renowned international organizations such as the Flemish Institute for Research and Technology (VITO), the Joint Research Centre (JRC) of the European Commission, the Research Institute of Wageningen University (Alterra), and the University of Milan (UNIMI) contribute to this system.

The CGMS-Maroc leverages cutting-edge technologies for data collection, agroclimatic modeling, and machine learning (Balaghi et al., 2024). It relies on 44 synoptic and 150 VigiObs ground-based meteorological stations, as well as satellite data (such as NDVI, LAI, and SWI) from the Copernicus program. Rainfall and temperature data are measured at a spatial resolution of 4.5 km × 4.5 km in agricultural areas and 9 km × 9 km in non-agricultural areas. The system stores data at both the grid level and aggregated district level (Lahlou, 2018).

Figure 5 illustrates the total annual rainfall (in millimeters) for each year. Notably, our communes received a two-year amount of rainfall in 2018. Additionally, we observe a gradual decrease in rainfall over time. Figure 6 provides a monthly breakdown of total rainfall, revealing a small decline in rainfall for each month.

Figure 5: Total Rainfall (mm) for Each Year

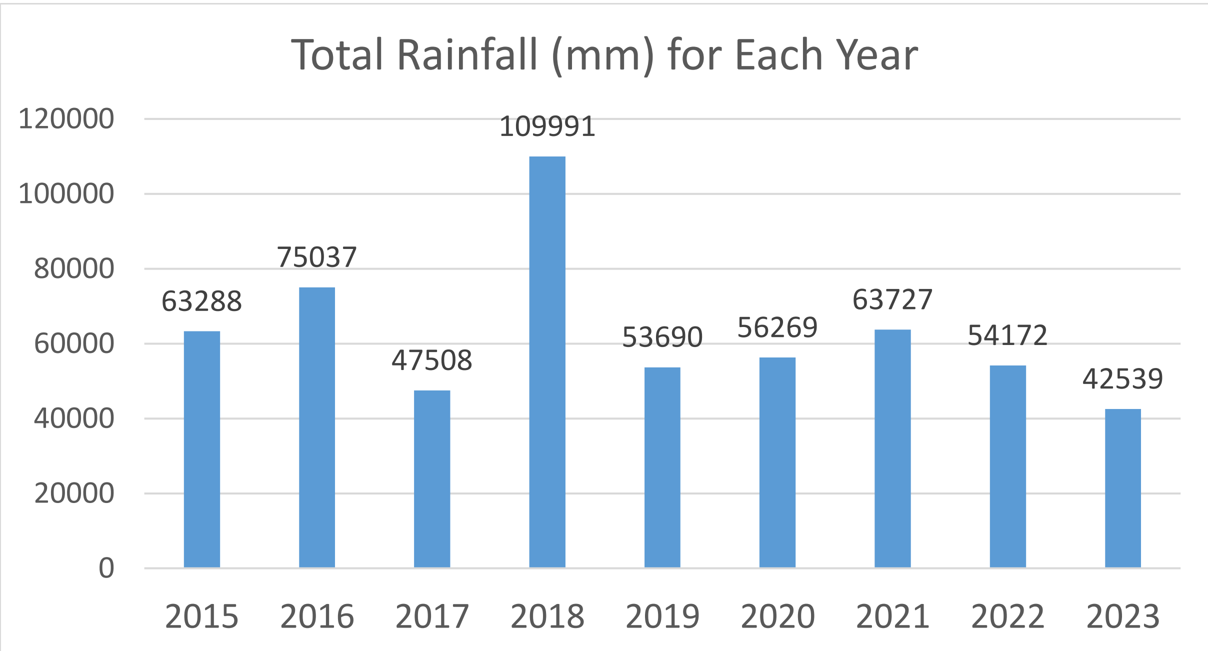
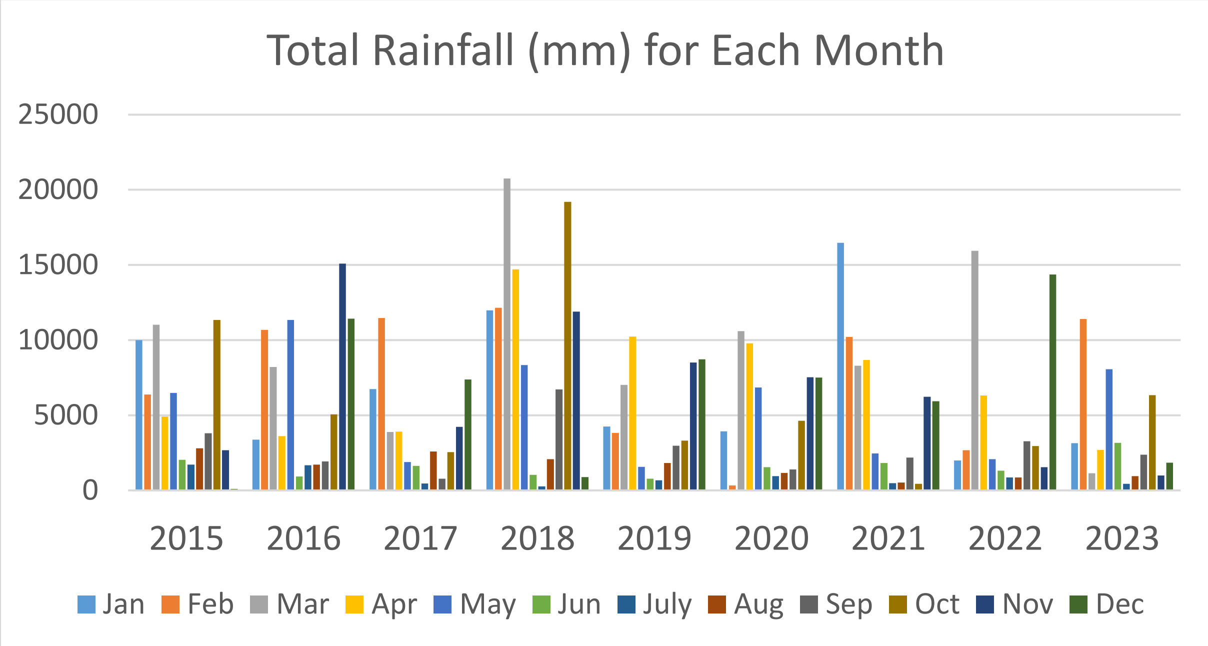


Figure 6: Total Rainfall (mm) for Each Month



We collected monthly rainfall data for each rural commune from January 2015 to December 2023. For every commune and month, we computed the total rainfall over the preceding 3 months, 6 months, 1 year, 2 years, and 3 years. For example, if we wanted to understand loan patterns in a specific commune in May 2016, we summed up the total rainfall from February 2016 to April 2016 as the 3-month prior total rainfall for that commune.

To assess rainfall shocks, we followed a method similar to Duflo and Pande (2007). First, we calculated the average total rainfall over the same time spans (3 months, 6 months, 1 year, 2 years, and 3 years) for each commune and month using our 9-year rainfall dataset. Next, we subtracted the actual rainfall values from these averages to obtain the rainfall difference. For instance, if a commune experienced 100 mm of actual rainfall in the past 3 months but had an average of 150 mm over the last 9 years, we considered this a negative rainfall shock of -50 mm for that commune in that specific month.

Figures 7 and 8 depict the average monthly rainfall (in millimeters) and its standard deviation, respectively. Meanwhile, Figures 9 and 10 showcase the average yearly rainfall (in millimeters) and its standard deviation. Additionally, the colorful regions highlight the communes in our dataset.

Figure 7: Average Monthly Rainfall (mm) in Rural Communes in Our Dataset

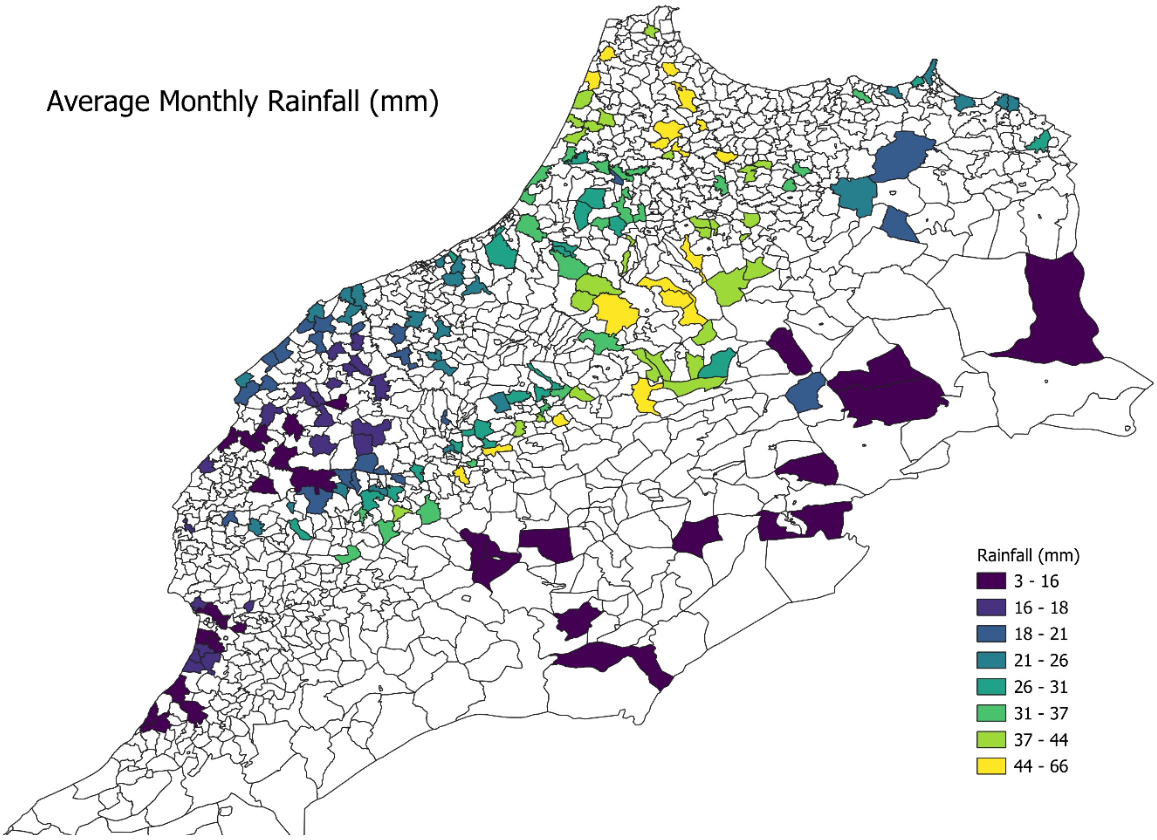


Figure 8: Standard Deviation of Monthly Rainfall (mm) in Rural Communes in Our Dataset

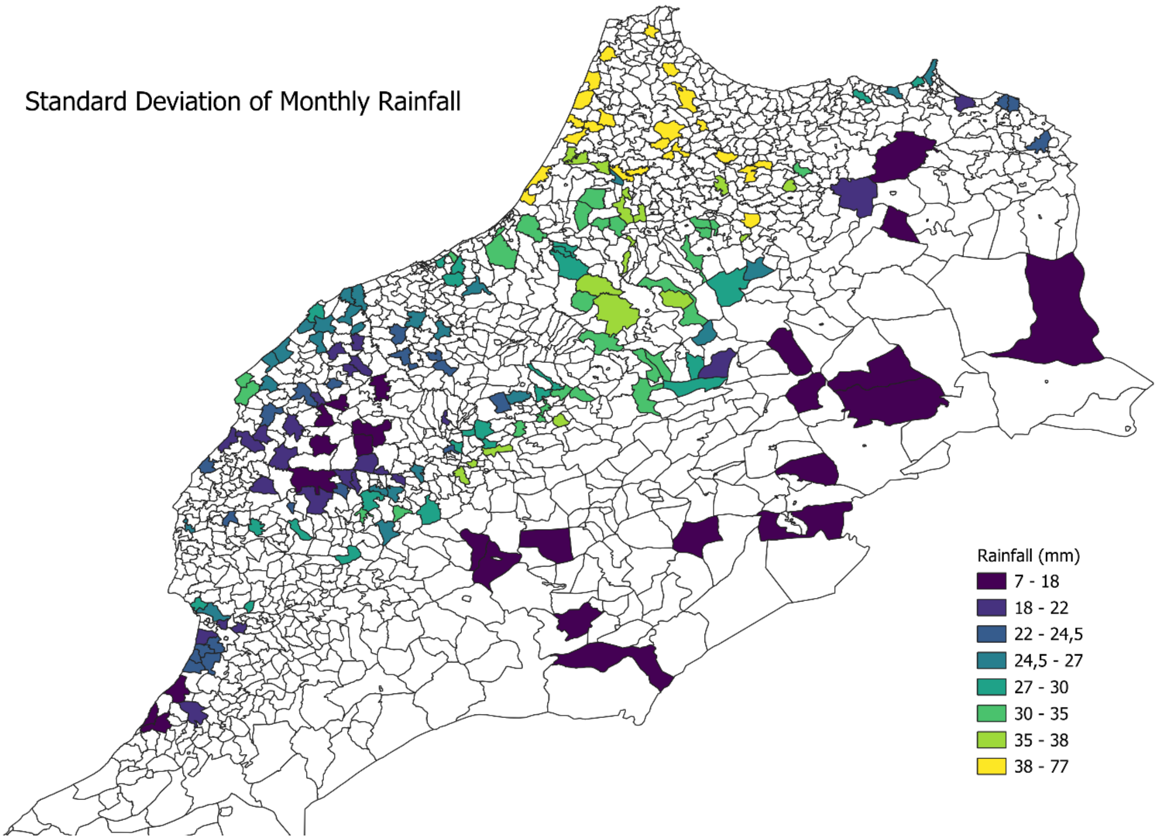


Figure 9: Average Yearly Rainfall (mm) in Rural Communes in Our Dataset

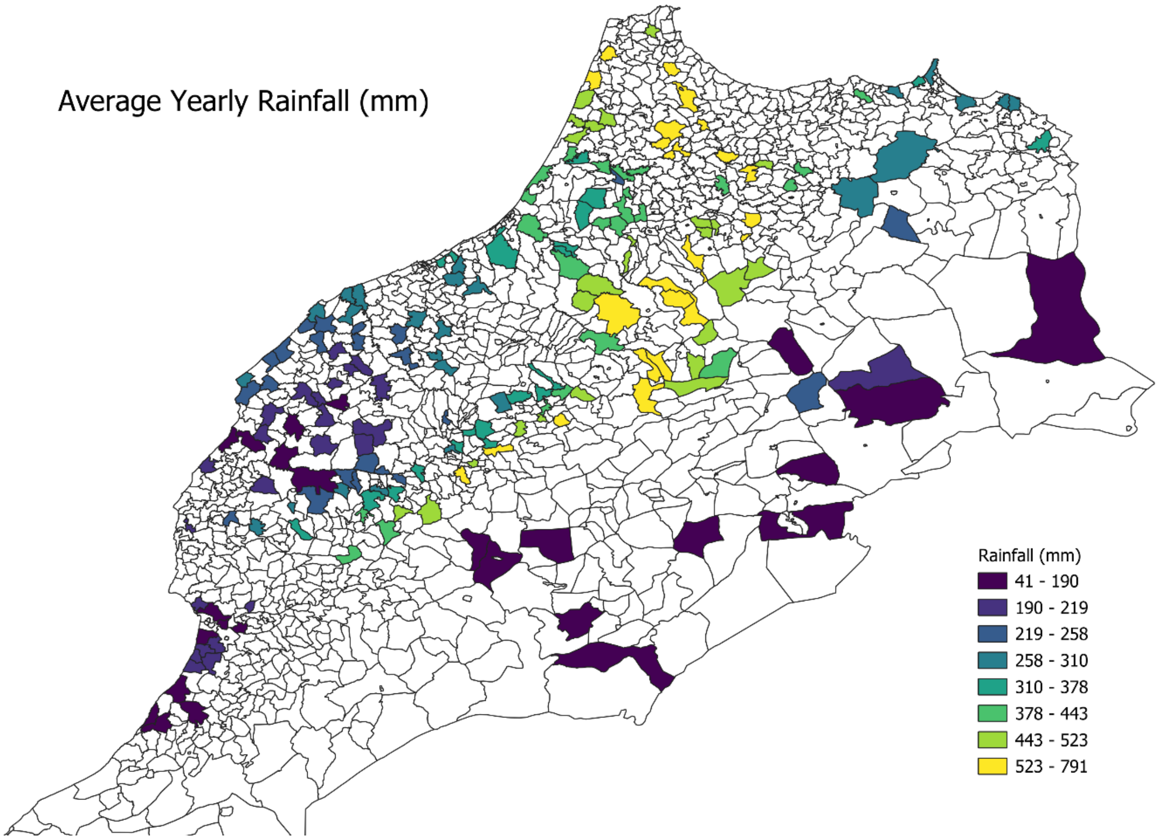
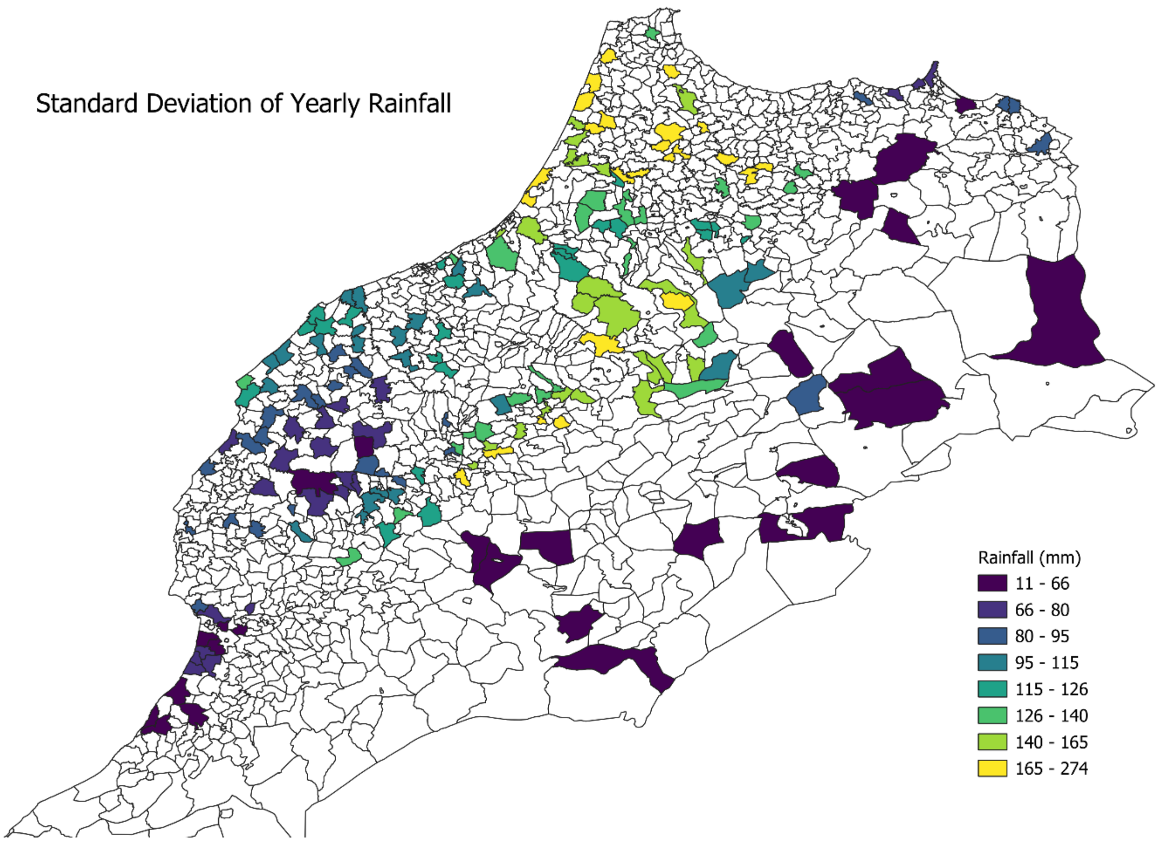


Figure 10: Standard Deviation of Yearly Rainfall (mm) in Rural Communes in Our Dataset



Lastly, The High Commission for Planning serves as the primary producer of official statistics in Morocco. For our analysis, we leveraged their Rural Municipal Inventory 2010/2011 database to identify explanatory variables for each rural commune. While this dataset may be somewhat dated, certain critical details—such as distance from urban centers and terrain characteristics—remain unchanged and continue to provide valuable insights.

Econometric Model

We aggregate our datasets to create a large panel dataset. Our goal is to explore the relationship between previous rainfall amounts and microcredit availability in rural Moroccan communes. Since each commune has unique characteristics, we opt for a fixed-effects panel model. Consequently, we employ a fixed-effects panel model to investigate how different durations of previous rainfall impact the number of loans taken within each commune. However, all other explanatory variables are specific to each commune. Fixed-effects models are consistent but do not accommodate group-level predictors that vary only between communes. For instance, we cannot analyse the relationship between population size and loan numbers using this approach.

To estimate the effect of commune-specific variables on microcredit, we turn to a random-effects model. Before applying this model, we conduct a Hausman test to assess its consistency and efficiency. The test yields a p-value of 0.0937, which is greater than 0.05. Consequently, we do not have strong evidence to reject the null hypothesis, suggesting that the random-effects model is consistent and may be preferable.

In other regression analyses, we consistently use the random-effects model. However, we employ the fixed-effects model when appropriate, given the plausible assumption that each commune exhibits distinct features.

In our dataset, we have precisely 71 potential commune-specific explanatory variables, excluding previous total rainfall data for various time intervals. Unfortunately, there is no universally accepted method for selecting the best explanatory variables. To identify the most relevant ones, we explored hundreds of combinations.

Ultimately, we settled on seven explanatory variables:

1. Population of Commune (Population)
2. Distance between Commune and Urban Centre (Distance)
3. Mountainous Terrain Indicator (Mountainous)
4. Number of Weekly Souks in Commune (WeeklySouk)
5. Number of Banking Agencies in Commune (BankingAgency)
6. Presence of an Industrial District in Commune (IndustrialDistrict)

7. Number of Factories in Commune (Factory)

Our dependent variable (y) is the number of loans taken in a specific month within each commune. We primarily focus on two types of explanatory (x) variables:

1. Previous Total Rainfall Amounts for Different Durations

2. Rainfall Shock Amounts for Different Durations

For instance, the ThreeMonthsRain variable represents the total rainfall over the last three months for a specific commune and month. In contrast, the ThreeMonthsShock variable captures the difference between the actual rainfall amount and the average rainfall over the same period for that commune and month. The variable names are chosen based on their specific time durations.

Rainfall Results

Table 7-11 presents the coefficients of each regressor, corresponding to total rainfall data from three months, six months, one year, two years, and three years prior. Standard deviations for each coefficient are provided in parentheses. Asterisks denote significant coefficients. The panel model specifies either a fixed effect or a random effect.

Our findings remain consistent regardless of the duration of prior total rainfall used. We observed a positive correlation between previous rainfall amounts and the number of loans taken in rural communes, significant at the 0.01 confidence level.

Several factors may contribute to this correlation. In rural areas of Morocco, water is fundamental to life, with agriculture heavily reliant on rainwater. Rainfall is not a random occurrence. When there is a higher amount of rainfall in the recent past, villagers may anticipate future rainfall. This expectation could lead them to believe that the trend of rainfall will continue, and taking a loan now would facilitate easier repayment in the future.

The economic situation of many villagers in rural Morocco is contingent on rainfall. An increase in past rainfall amounts often translates into higher income for these individuals. This increased income may incentivize them to borrow more money for investment purposes, such as purchasing productivity-enhancing tools, fertilizers, or cultivating crops. As highlighted in the introduction, previous studies (Cheng, 2007; Mohamed, 2008; Pariente, 2011; Li et al., 2011; Qin et al., 2019) have demonstrated that individuals are more likely to utilize microcredit when their income increases.

Increased rainfall leads to more grass and an abundance of insects and worms. While sheep and cattle rely on grass for sustenance, chickens can feed on insects and worms. By fostering the growth of these creatures, rural communities can reduce animal breeding costs. Consequently, people in rural areas may borrow more money and invest in new animals after heavy rain.

Moreover, the rise in rainfall can boost income for rural residents. For investors targeting this demographic, post-rain periods may be opportune times to borrow and invest. Consider a villager planning to establish a small flour mill: it would be more logical to do so after the rainy season rather than during a drought. Farmers tend to produce more after rain, which could attract more customers to the mill.

As expected, an increase in the population of a commune or the number of banking agencies within it correlates with a higher demand for loans. Mohamed (2008) found that Zanzibar farmers' microcredit demand positively relates to the number of bank accounts in their households.

Intriguingly, our research revealed that the presence of weekly souks (markets) and industrial districts in rural communes is associated with decreased demand for microcredit. It's possible that when people have alternative income sources, they rely less on loans. Additionally, areas with souks and industrial districts may be perceived as less financially risky. On the flip side, the number of factories within a commune positively correlates with the total number of microcredits issued.

Furthermore, souks and industrial districts play a role in fostering social networks. Borrowers may prefer informal lending within their community over formal microcredit institutions, reducing the need for external borrowing. However, if a commune is mountainous, it negatively impacts microcredit demand. In such regions, limited opportunities for agriculture and animal husbandry may hinder effective microcredit utilization.

Lastly, we observed that the distance between a commune and an urban center is inversely related to microcredit demand. This finding aligns with existing literature (Li et al., 2011).

Table 1: Regression results when rainfall (mm) of past three months is explanatory variable

VARIABLES	numberofloans	numberofloans	numberofloans	numberofloans	numberofloans
threemonthsrain	0.0147***	0.0146***	0.0146***	0.0146***	0.0146***
	(0.00180)	(0.00181)	(0.00181)	(0.00181)	(0.00181)
population		0.000396***	0.000353***	0.000282***	0.000284***
		(7.39e-05)	(7.34e-05)	(6.95e-05)	(7.56e-05)
distance			-0.0397**	-0.0371**	-0.0338**
			(0.0157)	(0.0156)	(0.0155)
mountainous			-3.728***	-4.213***	-4.530***
			(1.381)	(1.471)	(1.485)
weeklysouk				-2.399***	-2.263**
				(0.925)	(0.929)
bankingagency				4.922**	5.149***
				(2.134)	(1.988)
industrialdistrict					-7.829***
					(2.684)
factory					0.170***
					(0.0506)
Constant	22.47***	14.34***	17.66***	20.03***	19.98***
	(0.153)	(1.395)	(1.684)	(1.944)	(1.993)
Observations	12,485	12,485	12,485	12,485	12,485
R-squared	0.017				
Number of Communes	187	187	187	187	187
Panel Model	Fixed Effect	Random Effect	Random Effect	Random Effect	Random Effect
Wald chi2		77.83	98.99	127.2	293.3
Prob > chi2		0	0	0	0

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2: Regression results when rainfall (mm) of past six months is explanatory variable

VARIABLES	numberofloans	numberofloans	numberofloans	numberofloans	numberofloans
sixmonthsrain	0.0129***	0.0128***	0.0129***	0.0129***	0.0129***
	(0.00157)	(0.00157)	(0.00157)	(0.00157)	(0.00157)
population		0.000398***	0.000353***	0.000281***	0.000284***
		(7.46e-05)	(7.40e-05)	(7.02e-05)	(7.64e-05)
distance			-0.0391**	-0.0365**	-0.0331**
			(0.0160)	(0.0158)	(0.0157)
mountainous			-4.097***	-4.588***	-4.918***
			(1.381)	(1.471)	(1.485)
weeklysouk				-2.438***	-2.301**
				(0.931)	(0.934)
bankingagency				4.961**	5.201***
				(2.154)	(2.000)
industrialdistrict					-8.076***
					(2.688)
factory					0.170***
					(0.0508)
Constant	21.51***	13.37***	16.77***	19.17***	19.11***
	(0.268)	(1.427)	(1.712)	(1.978)	(2.026)
Observations	12,485	12,485	12,485	12,485	12,485
R-squared	0.025				
Number of Communes	187	187	187	187	187
Panel Model	Fixed Effect	Random Effect	Random Effect	Random Effect	Random Effect
Wald chi2		78.12	98.02	125.2	313.6
Prob > chi2		0	0	0	0
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Table 3: Regression results when rainfall (mm) of past one year is explanatory variable

VARIABLES	numberofloans	numberofloans	numberofloans	numberofloans	numberofloans
oneyearrain	0.0100***	0.00977***	0.00985***	0.00986***	0.00988***
	(0.00167)	(0.00166)	(0.00166)	(0.00166)	(0.00166)
population		0.000399***	0.000353***	0.000280***	0.000284***
		(7.54e-05)	(7.49e-05)	(7.12e-05)	(7.76e-05)
distance			-0.0379**	-0.0354**	-0.0318**
			(0.0166)	(0.0162)	(0.0161)
mountainous			-4.547***	-5.048***	-5.395***
			(1.399)	(1.488)	(1.506)
weeklysouk				-2.493***	-2.354**
				(0.942)	(0.945)
bankingagency				5.007**	5.264***
				(2.179)	(2.016)
industrialdistrict					-8.406***
					(2.696)
factory					0.169***
					(0.0512)
Constant	20.24***	12.16***	15.62***	18.07***	17.99***
	(0.579)	(1.474)	(1.760)	(2.043)	(2.092)
Observations	12,485	12,485	12,485	12,485	12,485
R-squared	0.019				
Number of Communes	187	187	187	187	187
Panel Model	Fixed Effect	Random Effect	Random Effect	Random Effect	Random Effect
Wald chi2		55.01	73.68	98.33	274.3
Prob > chi2		0	0	0	0
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Table 4: Regression results when rainfall (mm) of past two years is explanatory variable

VARIABLES	numberofloans	numberofloans	numberofloans	numberofloans	numberofloans
twoyearsrain	0.0159***	0.0151***	0.0152***	0.0152***	0.0152***
	(0.00198)	(0.00192)	(0.00193)	(0.00192)	(0.00193)
population		0.000405***	0.000350***	0.000272***	0.000284***
		(8.17e-05)	(8.13e-05)	(7.86e-05)	(8.59e-05)
distance			-0.0320	-0.0295	-0.0255
			(0.0215)	(0.0207)	(0.0205)
mountainous			-7.211***	-7.751***	-8.190***
			(1.646)	(1.722)	(1.750)
weeklysouk				-2.764**	-2.617**
				(1.100)	(1.097)
bankingagency				5.254**	5.610***
				(2.361)	(2.151)
industrialdistrict					-10.27***
					(2.907)
factory					0.165***
					(0.0554)
Constant	12.62***	4.909**	8.884***	11.59***	11.42***
	(1.384)	(1.910)	(2.228)	(2.508)	(2.550)
Observations	12,485	12,485	12,485	12,485	12,485
R-squared	0.070				
Number of Communes	187	187	187	187	187
Panel Model	Fixed Effect	Random Effect	Random Effect	Random Effect	Random Effect
Wald chi2		75.50	91.36	113.7	374.8
Prob > chi2		0	0	0	0
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Table 5: Regression results when rainfall (mm) of past three years is explanatory variable

VARIABLES	numberofloans	numberofloans	numberofloans	numberofloans	numberofloans
threeyearsrain	0.0149***	0.0135***	0.0137***	0.0136***	0.0137***
	(0.00166)	(0.00155)	(0.00156)	(0.00155)	(0.00156)
population		0.000409***	0.000348***	0.000267***	0.000284***
		(8.56e-05)	(8.54e-05)	(8.31e-05)	(9.08e-05)
distance			-0.0293	-0.0267	-0.0225
			(0.0247)	(0.0238)	(0.0236)
mountainous			-8.609***	-9.159***	-9.645***
			(1.852)	(1.915)	(1.949)
weeklysouk				-2.882**	-2.730**
				(1.220)	(1.215)
bankingagency				5.420**	5.823***
				(2.469)	(2.240)
industrialdistrict					-11.18***
					(3.113)
factory					0.163***
					(0.0586)
Constant	7.877***	1.072	5.238**	8.084***	7.864***
	(1.757)	(2.145)	(2.491)	(2.750)	(2.796)
Observations	12,485	12,485	12,485	12,485	12,485
R-squared	0.069				
Number of Communes	187	187	187	187	187
Panel Model	Fixed Effect	Random Effect	Random Effect	Random Effect	Random Effect
Wald chi2		87.24	100.5	119.6	370.3
Prob > chi2		0	0	0	0
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Rainfall Shock Results

As previously mentioned, the “ThreeMonthsRain” variable represents the total rainfall over the last three months for a specific commune and month. In contrast, the “ThreeMonthsShock” variable captures the deviation between the actual rainfall amount and the average rainfall over the same period for that commune and month.

To calculate the “ThreeMonthsShock %” variable, we divide the difference between the actual rainfall amount and the average rainfall by the average rainfall amount for the same period in that specific commune and month. For example, if the “ThreeMonthsShock %” equals 0.5 in a particular commune and month, it indicates a 50% increase in rainfall compared to the nine-year average for the same period. The variable names are chosen based on their specific time durations.

Table 6 illustrates the percentage rainfall shock variables for different durations. Notably, as time durations decrease, communities may experience more extreme fluctuations in rainfall. Conversely, when time durations increase, rainfall shocks tend to be milder.

Additionally, it's worth noting that the median (p50) of the "ThreeMonthsShock %" variable is smaller than the 25th percentile (p25) of the "TwoYearsShock %" and "ThreeYearsShock %" variables.

Table 6: Descriptive statistics for percentage rainfall shock variables for different durations

VARIABLES	N	mean	sd	min	max	p10	p25	p50	p75	p90
threemonthsshock %	12,485	-0.00299	0.576	-0.992	3.403	-0.626	-0.398	-0.123	0.256	0.800
sixmonthsshock %	12,485	0.0206	0.446	-0.946	2.554	-0.463	-0.274	-0.0695	0.252	0.648
oneyearshock %	12,485	0.0214	0.310	-0.777	1.252	-0.309	-0.203	-0.0511	0.196	0.469
twoyearsshock %	12,485	0.0316	0.195	-0.511	0.678	-0.212	-0.116	0.00351	0.196	0.303
threeyearsshock %	12,485	0.0481	0.142	-0.305	0.431	-0.139	-0.0749	0.0513	0.158	0.236

In this section, we analyze the impact of rainfall shocks on microcredit demand by examining differences from average normal rainfall amounts for various durations. We incorporate the same explanatory variables used in the previous rainfall results section. Remarkably, our findings remain consistent across different prior total rainfall durations. Specifically, as the deviation between actual and average rainfall increases, the number of loans taken in rural communes also rises. In the preceding section, we explored potential reasons for this observed relationship. In the context of droughts, individuals often struggle to earn sufficient income, leading to an increased need for financial support. To explore the impact of positive and negative rainfall shocks on microcredit demand, we segmented our sample into two categories: positive rainfall shocks and negative rainfall shocks for each duration. Remarkably, we observed a consistent positive relationship in the subsample affected by only positive rainfall shocks.

However, in the subsample experiencing only negative rainfall shocks, the sign of coefficients changed. Specifically, for short-duration variables, the sign changes occur around the p50 percentile. As the time duration increases, the percentile at which the coefficient sign changes decreases. This phenomenon may be related to the fact that shorter time durations lead to more extreme fluctuations in community rainfall, while longer durations result in milder shocks. Consequently, we can infer that microcredit demand does not immediately increase during the early days of a negative rainfall shock; instead, demand begins to rise as the severity of the shock intensifies. We found that as the level of negative rainfall shock increases, the total number of loans taken also rises. Additionally, the effect of negative rainfall shocks on microcredit demand becomes more pronounced as drought severity increases. Initially, people may fear the consequences of not repaying a loan. However, beyond a certain threshold, they become desperate to secure a loan.

Table 7: The effect of a past three-months rainfall shock on different samples

	(all sample)	(only positive)	(only negative)	(25 percentile)
VARIABLES	numberofloans	numberofloans	numberofloans	numberofloans
threemonthsshock	0.0164***	0.0201***	-0.0168***	-0.0446***
	(0.00252)	(0.00351)	(0.00489)	(0.00743)
population	0.000283***	0.000289***	0.000279***	0.000288***
	(7.48e-05)	(7.64e-05)	(7.49e-05)	(7.36e-05)
distance	-0.0346**	-0.0298*	-0.0361**	-0.0388***
	(0.0153)	(0.0170)	(0.0147)	(0.0142)
mountainous	-4.054***	-4.577***	-4.025***	-4.558***
	(1.489)	(1.674)	(1.400)	(1.455)
weeklysouk	-2.227**	-2.518**	-2.057**	-1.974**
	(0.927)	(0.999)	(0.905)	(0.936)
bankingagency	5.089**	5.778***	4.665**	4.784**
	(1.978)	(2.063)	(1.940)	(1.979)
industrialdistrict	-7.527***	-8.774***	-6.744**	-6.525**
	(2.692)	(2.522)	(2.865)	(2.871)
factory	0.171***	0.171***	0.171***	0.185***
	(0.0505)	(0.0524)	(0.0506)	(0.0474)
Constant	21.07***	21.38***	19.98***	18.18***
	(1.958)	(2.069)	(1.937)	(1.985)
Observations	12,485	5,010	7,475	3,118
Number of Communes	187	187	187	187
Panel Model	Random Effect	Random Effect	Random Effect	Random Effect
Wald chi2 (8)	243.5	249.2	216.3	315.5
Prob > chi2	0	0	0	0

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8: The effect of a past six-months rainfall shock on different samples

	(all sample)	(only positive)	(only negative)	(25 percentile)
VARIABLES	numberofloans	numberofloans	numberofloans	numberofloans
sixmonthsshock	0.0159***	0.0125***	0.00416	-0.0319***
	(0.00226)	(0.00295)	(0.00372)	(0.00673)
population	0.000283***	0.000291***	0.000280***	0.000263***
	(7.49e-05)	(8.06e-05)	(7.21e-05)	(7.34e-05)
distance	-0.0345**	-0.0322*	-0.0358**	-0.0369**
	(0.0153)	(0.0179)	(0.0141)	(0.0146)
mountainous	-4.064***	-4.913***	-3.574***	-4.515***
	(1.489)	(1.701)	(1.374)	(1.328)
weeklysouk	-2.242**	-2.675***	-1.947**	-1.998**
	(0.927)	(1.025)	(0.893)	(0.922)
bankingagency	5.099***	5.660***	4.759**	4.776**
	(1.979)	(2.101)	(1.909)	(1.891)
industrialdistrict	-7.548***	-8.898***	-6.621**	-6.858**
	(2.691)	(2.633)	(2.832)	(2.790)
factory	0.171***	0.177***	0.163***	0.187***
	(0.0506)	(0.0564)	(0.0477)	(0.0486)
Constant	21.04***	22.09***	20.03***	18.02***
	(1.958)	(2.134)	(1.912)	(2.034)
Observations	12,485	5,353	7,132	3,125
Number of Communes	187	187	187	187
Panel Model	Random Effect	Random Effect	Random Effect	Random Effect
Wald chi2 (8)	244.7	199.6	202.3	246.7
Prob > chi2	0	0	0	0
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Table 9: The effect of a past one-year rainfall shock on different samples

	(all sample)	(only positive)	(only negative)	(25 percentile)
VARIABLES	numberofloans	numberofloans	numberofloans	numberofloans
oneyearshock	0.0100***	0.00741***	-0.00324	-0.0420***
	(0.00168)	(0.00228)	(0.00304)	(0.00782)
population	0.000283***	0.000276***	0.000289***	0.000296***
	(7.49e-05)	(8.05e-05)	(7.23e-05)	(7.57e-05)
distance	-0.0344**	-0.0289	-0.0346**	-0.0264*
	(0.0154)	(0.0180)	(0.0141)	(0.0154)
mountainous	-4.073***	-4.968***	-3.537***	-5.259***
	(1.490)	(1.712)	(1.355)	(1.442)
weeklysouk	-2.250**	-2.588**	-1.956**	-1.692*
	(0.927)	(1.039)	(0.871)	(0.930)
bankingagency	5.096**	5.125***	5.173**	5.815***
	(1.981)	(1.921)	(2.031)	(2.082)
industrialdistrict	-7.562***	-8.303***	-7.136**	-8.359***
	(2.688)	(2.536)	(2.907)	(2.763)
factory	0.171***	0.166***	0.176***	0.163***
	(0.0506)	(0.0527)	(0.0507)	(0.0486)
Constant	21.04***	22.24***	19.41***	15.41***
	(1.958)	(2.126)	(1.885)	(2.093)
Observations	12,485	5,572	6,913	3,135
Number of Communes	187	187	187	187
Panel Model	Random Effect	Random Effect	Random Effect	Random Effect
Wald chi2 (8)	240.4	206.8	182.7	276.9
Prob > chi2	0	0	0	0
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Table 10: The effect of a past two-years rainfall shock on different samples

	(all sample)	(only positive)	(only negative)	(25 percentile)	(10 percentile)
VARIABLES	numberofloans	numberofloans	numberofloans	numberofloans	numberofloans
twoyearsshock	0.0159***	0.00380	0.0111***	0.00265	-0.0163
	(0.00199)	(0.00251)	(0.00262)	(0.00480)	(0.0111)
population	0.000281***	0.000274***	0.000291***	0.000281***	0.000295***
	(7.52e-05)	(8.52e-05)	(7.06e-05)	(6.84e-05)	(6.96e-05)
distance	-0.0333**	-0.0338*	-0.0334**	-0.0275**	-0.0266*
	(0.0156)	(0.0189)	(0.0139)	(0.0136)	(0.0143)
mountainous	-4.127***	-5.782***	-2.837**	-3.198**	-2.838**
	(1.507)	(1.813)	(1.300)	(1.258)	(1.421)
weeklysouk	-2.298**	-2.869**	-1.642*	-1.717**	-1.585*
	(0.931)	(1.139)	(0.872)	(0.860)	(0.920)
bankingagency	5.092**	5.018**	4.883**	4.866**	6.601***
	(1.988)	(1.962)	(2.050)	(2.208)	(2.320)
industrialdistrict	-7.684***	-9.328***	-6.394**	-5.491*	-7.446**
	(2.664)	(2.635)	(2.999)	(2.931)	(3.003)
factory	0.170***	0.194***	0.151***	0.196***	0.151**
	(0.0505)	(0.0559)	(0.0501)	(0.0530)	(0.0597)
Constant	20.80***	24.34***	19.07***	17.72***	14.70***
	(1.963)	(2.362)	(1.876)	(1.978)	(2.428)
Observations	12,485	6,344	6,141	3,120	1,240
Number of Communes	187	187	187	187	181
Panel Model	Random Effect	Random Effect	Random Effect	Random Effect	Random Effect
Wald chi2 (8)	304.7	214.6	164.2	144.3	136.4
Prob > chi2	0	0	0	0	0
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Table 11: The effect of a past three-years rainfall shock on different samples

	(all sample)	(only positive)	(only negative)	(25 percentile)	(10 percentile)
VARIABLES	numberofloans	numberofloans	numberofloans	numberofloans	numberofloans
threeyearsshock	0.0149***	0.0100***	0.00853**	-0.00724	-0.0421***
	(0.00166)	(0.00224)	(0.00374)	(0.00605)	(0.0109)
population	0.000279***	0.000288***	0.000284***	0.000282***	0.000315***
	(7.50e-05)	(8.20e-05)	(7.05e-05)	(6.89e-05)	(9.36e-05)
distance	-0.0328**	-0.0336*	-0.0318**	-0.0328**	-0.0187
	(0.0156)	(0.0182)	(0.0132)	(0.0131)	(0.0144)
mountainous	-4.175***	-5.253***	-2.691**	-3.092**	-5.839***
	(1.502)	(1.742)	(1.274)	(1.258)	(1.711)
weeklysouk	-2.303**	-2.773***	-1.627*	-1.319	-1.769
	(0.929)	(1.057)	(0.880)	(0.924)	(1.248)
bankingagency	5.129***	5.536***	4.602**	5.623***	6.699**
	(1.985)	(1.983)	(2.049)	(2.116)	(2.892)
industrialdistrict	-7.691***	-9.561***	-5.524*	-4.326	-7.591
	(2.660)	(2.732)	(3.002)	(2.957)	(6.876)
factory	0.171***	0.178***	0.162***	0.149***	0.112
	(0.0502)	(0.0530)	(0.0512)	(0.0564)	(0.0881)
Constant	20.47***	22.02***	18.50***	16.49***	10.90***
	(1.955)	(2.172)	(1.918)	(1.969)	(2.810)
Observations	12,485	7,406	5,079	3,118	1,258
Number of Communes	187	187	187	185	130
Panel Model	Random Effect	Random Effect	Random Effect	Random Effect	Random Effect
Wald chi2 (8)	328.1	261.4	142	116.1	85.06
Prob > chi2	0	0	0	0	0
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Discussion

Table 12: The effect of a future rainfall in today

VARIABLES	numberofloans	numberofloans
threemonthsrain (future)	0.00493***	
	(0.00159)	
population	0.000285***	0.000283***
	(7.60e-05)	(7.66e-05)
distance	-0.0343**	-0.0353**
	(0.0159)	(0.0161)
mountainous	-4.273***	-4.262***
	(1.535)	(1.566)
weeklysouk	-2.248**	-2.264**
	(0.947)	(0.963)
bankingagency	5.222***	5.204***
	(1.969)	(1.951)
industrialdistrict	-7.977***	-8.028***
	(2.689)	(2.694)
factory	0.170***	0.172***
	(0.0506)	(0.0512)
sixmonthsshock (future)		0.0172***
		(0.00199)
Constant	21.06***	21.86***
	(1.991)	(2.020)
Observations	11,741	11,183
Number of i	187	187
Wald chi2 (8)	196.2	283.8
Prob > chi2	0	0
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

Up until this point, our analysis has focused on estimating and explaining the number of microcredits in specific communes and months using past real rainfall data or past rainfall shocks. To assess the robustness of our rainfall estimator, we decided to estimate the number of microcredits in the same communes and months using future real rainfall data or future rainfall shocks.

Surprisingly, Table 12 reveals a positive relationship between future rainfall data and past microcredit demand. Logically, future rainfall should not be related to past microcredit demand, but our results suggest otherwise. In typical circumstances, we would be concerned about endogeneity—the correlation between an independent variable and the unexplained variation (or "error") in the dependent variable. To address this issue, we may consider using an instrumental variable (IV) estimator.

Both rainfall data and microcredit data are time series, particularly within the same commune. Since they are part of the same yearly repeating climate, there is a strong correlation. For instance, the total rainfall amount over the last three months may be statistically significant in predicting the total rainfall amount over the next six months. Surprisingly, this correlation suggests that future rainfall in a given commune affects past microcredit demand in that same commune.

To address this potential endogeneity issue, I conducted the Granger causality test. This statistical test assesses whether one time series can predict another. Specifically, I examined the relationship between rainfall time series data and microcredit demand time series data across several communes. The results indicate that rainfall data influences microcredit demand, but not vice versa.

Figure 11: An example of Granger Causality test (r1 is rainfall, m1 is microcredit)

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
m1	r1	6.8205	2	0.033
m1	ALL	6.8205	2	0.033
r1	m1	.14142	2	0.932
r1	ALL	.14142	2	0.932

Conclusion

In our study, we obtained an extensive microcredit dataset from Al Amana, the largest microfinance institution in Morocco. Additionally, we acquired highly accurate rainfall data from the CGMS-Maroc (Crop Growth Monitoring System). By calculating the number of loans taken in each rural commune per month, we combined this information with rainfall data and additional explanatory variables from The High Commission for Planning, which serves as the primary producer of official statistics in Morocco. Our analysis, using a panel data random effects model, revealed a statistically significant positive correlation between previous rainfall amounts and the number of loans taken in rural communes, with significance at the 0.01 confidence level.

As expected, an increase in the population of a commune or the number of banking agencies within it correlates with a higher demand for loans. Intriguingly, our research also revealed that the presence of weekly souks (markets) and industrial districts in rural communes is associated with decreased demand for microcredit. On the flip side, the number of factories within a commune positively correlates with the total number of microcredits issued. Additionally, we observed that the distance between a commune and an urban center is inversely related to microcredit demand.

In our study, we investigated the impact of positive and negative rainfall shocks on microcredit demand. To do so, we divided our sample into two categories: those affected by positive rainfall shocks and those affected by negative rainfall shocks for each duration.

Remarkably, we consistently observed a positive relationship in the subsample affected by only positive rainfall shocks. However, in the subsample experiencing only negative rainfall shocks, the sign of coefficients changed. Specifically, for short-duration variables, the sign changes occurred around the p50 percentile. As the time duration increased, the percentile at which the coefficient sign changed decreased.

From these findings, we can infer that microcredit demand does not immediately increase during the early days of a negative rainfall shock. Instead, demand begins to rise as the severity of the shock intensifies.

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