



Article

# Weather Shocks and Banking Credit Risk: Evidence for Small Rural Municipalities in Colombia

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## Abstract

This paper studies the impact of weather shocks on the credit risk of bank portfolios in small and rural municipalities in Colombia, which are highly vulnerable to these climate variations. It addresses the relationship between extreme temperature and precipitation events and the increase in the proportion of loans at risk, using data from 2011 to 2023. Extreme climate shocks negatively affect loan portfolio quality in Colombian rural municipalities, especially in microcredits. Credit risk decreases in municipalities with higher per capita incomes. It varies according to the type of loan and the nature of the weather shock. The results show that low temperature shocks increase risk in commercial and consumer loans. In contrast, low-precipitation shocks increase risk in microcredit. The increasing importance of climatic disturbances stresses the need for banks to develop their own models to manage these risks and to deepen analysis that incorporate borrower-specific information and banking policies to protect both financial institutions and borrowers from the impacts of climate change. The integration of sustainable practices and climate education can be key to improving financial resilience in these vulnerable areas.

**Keywords:** banking credit risk; weather shocks; microcredit; financial resilience; Colombia

**JEL Classification:** G21; G32; Q54



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## 1. Introduction

The undeniable impact of greenhouse gases and human activities is causing imbalances in all the planet's ecosystems, generating an emerging and widespread climate risk that affects all types of human activities. Some of the United Nations' sustainable development goals (SDGs) directly look to maintaining the ecosystem's viability and avoiding increasing the planet's average temperature beyond 1.5 °C above pre-industrial levels. As a result, countries and companies are making considerable efforts to mitigate the negative impact of human activities. Unfortunately, there are delays in most of the goals, and the emissions gap report of the UN ([UN Environment Programme, 2022](https://www.unep.org/unep-press/publications/emissions-gap-report-2022)) expresses doubts about the possibility of reaching 2050 with an increase in temperature in line with the goal.

Although not directly involved in productive activities, the financial sector provides resources for agricultural activities. Therefore, allocating these funds will affect the achievement of the SDGs. On the other hand, the credit quality will also be affected by climate

change. Prolonged droughts, excessively wet seasons, or continuous periods with extreme temperatures impact the ability of a large proportion of debtors to meet their commitments. As one of the consequences of climate change is that the probability of recurrence of extreme weather events is increasing, its impact on the quality of the banking portfolio will surely increase in the near future.

Both regulators and banks seek the general stability of the financial system as a whole and, of course, for each bank in particular, so risk management systems and requirements must consider the impact of all types of risks in general and, in particular, those associated with climate change. Since the impact of climate change is relatively recent, how the portfolio of credit institutions may behave in the face of these events is an open question, and the tools for their management are indeed incipient. This research focuses on this impact to close this knowledge gap.

Our purpose is to study the impact of weather shocks on the riskiness of bank loans. Climate change, materialized as severe weather shocks, emerges as one of the main concerns by customers, credit institutions and governments alike. To this end, we structured a database of bank loans between 2011 and 2023 focused on small Colombian municipalities, far from large urban centers and whose vocation is eminently agricultural. Our data includes information on individual loans, their type (Commercial, Consumer, Microcredit, and Housing), lending bank, and location. It is natural to consider that loans granted in regions or municipalities concentrated on agricultural activities may be the most affected by external climatic events. Although Internet presence has reduced the importance of physical offices, just a few banks serve the rural credit market in Colombia. In this context, Banco Agrario, a state bank whose specific market is agriculture, is the dominant bank and a relevant subject of study for this research. The climatic data comes from Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) and Copernicus at the municipality level.

Our empirical strategy allows us to find that weather shocks tend to increase at-risk loans, with these effects being less severe in municipalities with higher per capita income levels. In summary, the evidence points out that low-temperature shocks and shocks that result in low-precipitation and high-temperature (droughts) tend to be associated with increases in the portfolio at risk, particularly for microcredit. The harmful effects of droughts on crops (diseases and crop losses) and human health (diseases and lower worker productivity) (Meierrieks, 2021; Cohen et al., 2021; Liliane & Charles, 2020; Thakur et al., 2010) explain this relationship. Climate shocks thus produce a negative shock to individuals' incomes and their ability to meet loan payments.

The remainder of the paper structure follows. Section 2 discusses the literature and presents our working hypotheses. Section 3 presents the data, the key institutional details of the rural credit market in Colombia, and Section 4 presents our empirical strategy. Section 5 discusses the results, and Section 6 concludes the study.

## 2. Literature Review

The relationship between climate hazards and default rates in banking is a complex connection influenced by various factors, including the type and intensity of climate events such as extreme rainfall and droughts (Castro & Garcia, 2014). These events can significantly impact borrowers' creditworthiness and financial institutions' stability. Extreme weather events, such as heavy rain and tropical cyclones, have been shown to increase delinquency rates. A study on a Chinese bank found that extreme weather shocks led to higher delinquency rates, although borrowers with prior exposure showed resilience and lower delinquency propensity (Chen et al., 2024). Similarly, in Florida, heavy rains and tropical cyclones significantly impacted mortgage default rates, with the intensity of cyclones

correlating with increased default risks (Calabrese et al., 2024). The agricultural sector is particularly vulnerable to climate hazards, as seen in Mexico, where extreme temperatures increase delinquency rates, affecting both agricultural and non-agricultural sectors reliant on local demand (Aguilar-Gomez et al., 2024). In Brazil, deviations in temperature and precipitation were linked to higher default rates, especially in agriculture, due to reduced income from climate-affected production (Oliveira, 2022).

Heavy rainfall, especially in flood-prone areas, exacerbates mortgage default risks. The interaction between flood risk and heavy rainfall significantly increased default probabilities in Florida, with future climate change scenarios predicting a systematic rise in such risks (Calabrese et al., 2024). Additionally, extreme rainfall influences corporate financing policies, prompting firms to adjust their debt structures and cash reserves to mitigate operational disruptions (Chen et al., 2024). Droughts, particularly in regions heavily dependent on agriculture, can lead to increased default rates due to reduced agricultural output and income. Oliveira (2022) found that in Brazil, severe droughts in the Northeast region led to higher delinquency rates in the agricultural sector.

Banks and borrowers with prior exposure to climate events often develop adaptive strategies that enhance resilience. For example, Chinese banks tend to extend more loans to regions affected by extreme weather without significantly increasing credit spreads, indicating a strategic approach to managing climate risks (Chen et al., 2024). Similarly, banks that integrate climate risk into their decision-making processes exhibit lower non-performing loan ratios, highlighting the importance of strategic risk management (Brik, 2024). Implementing climate stress tests and scenario analyses can help banks better understand and prepare for the impacts of extreme weather on default rates. For instance, a framework for integrating extreme weather risk into residential mortgage loans suggests that banks could face significant losses due to default correlation and property damage, emphasizing the need for robust stress testing (Wong & Ho, 2023). Additionally, financial adaptation through catastrophe bonds and disaster insurance can reduce welfare losses from climate-related disasters by about 25% (Phan & Schwartzman, 2023). In New Zealand, Greig et al. (2019) have found that firm managers' individual characteristics are good predictors of future debt repayment. Thus, bankers would benefit from using this individual information to better model commercial loan default.

Climate change introduces physical risks (e.g., storms and floods) and transition risks (e.g., policy changes) that can affect banks' credit risk profiles. These risks can lead to property damage and increased default rates, posing significant challenges to financial stability (Anderson et al., 2021). Typhoon damages in the Philippines led to a significant increase in non-performing loans, highlighting the persistent impact of such events on bank balance sheets (Nie et al., 2023).

Growing evidence shows that severe climate-related disasters lead to rising non-performing loans across banking systems. However, these relationships are nuanced and influenced by various factors such as geographic location, sectoral dependencies, and the adaptive capacities of financial institutions. The banking sector's response to these challenges varies, with some banks increasingly incorporating climate risks into their lending practices. However, significant gaps remain in understanding and managing these risks (Wu et al., 2023). Moreover, the impact of climate change on default rates is not uniform across regions or sectors, with developing countries often being more vulnerable due to limited adaptive capacities (Oliveira, 2022). As climate variability intensifies, it becomes essential for banks to incorporate climate risk into their financial strategies and risk management frameworks to enhance resilience and ensure financial stability.

Relevant research questions arise:

**RQ1:** How do different types of credit portfolios (commercial, consumer, and micro-credits) vary in their sensitivity to distinct weather shocks (rainfall vs. droughts) within rural, agriculture-dependent economies?

**RQ2:** What are the distinct impacts of contemporaneous versus temporal delays (lagged effects) on credit default rates?

**RQ3:** To what extent do regional economic buffers, specifically municipal per capita income levels or distance to natural markets, mitigate or intensify the adverse effects of extreme climate shocks on loan portfolio risk?

To answer research questions RQ1 and RQ2, we proceed to establish the following hypotheses:

**Hypothesis 1.** *Low-precipitation (H1a) and high-precipitation (H1b) shocks increase credit risk.*

**Hypothesis 2.** *Low-temperature (H2a) and high-temperature (H2b) shocks increase credit risk.*

**Hypothesis 3.** *Lagged low-precipitation (H3a) and lagged high-precipitation (H3b) shocks increase credit risk more than contemporaneous equivalent shocks.*

**Hypothesis 4.** *Lagged low-temperature (H4a) and lagged high-temperature (H4b) shocks increase credit risk more than contemporaneous equivalent shocks.*

Alternative definitions of weather shocks (see Section 3.2) based on the SPEI produce equivalent hypothesis based on drought and rainy shocks.

**Hypothesis 5.** *Drought (H5a) and Rainy (H5b) shocks increase credit risk.*

**Hypothesis 6.** *Lagged drought (H6a) and lagged rainy (H6b) shocks increase credit risk more than contemporaneous equivalent shocks.*

Research question RQ3 elicits our final working hypotheses:

**Hypothesis 7.** *Per capita income reduces credit risk, by providing a buffer to cope with reduced cash flows from weather shocks.*

**Hypothesis 8.** *Distance to natural markets increases credit risk, by increasing distribution and supplying costs of distant municipalities.*

We now proceed by describing our data.

### 3. Data

This section outlines the data sources, structure and variable definitions we use to test the credit risk dynamics. Our main data comprises aggregate volume from individual loans spanning from 2011 to 2023 downloaded from the Colombian Financial Superintendence (CFS, from now on), the financial regulator. Credit risk definitions also come from the CFS. The observation window stops at the latest available economic information required to build our control variables.

#### 3.1. Credit Data

We use CFS quarterly data on the balances of the credit portfolios for each credit institution in each municipality of the country. We work with information from four credit portfolios: Commercial, Consumer, Housing, and Microcredits. Each loan has the

following risk level: Normal, Acceptable, Deficient, Difficult to Collect, Uncollectible. Each credit institution must follow the methodology established by the CFS. A general way of describing each risk level follows:

- Normal: Credits rated in this category reflect appropriate structuring and attention. The debtors' financial statements, or the project's cash flows, and other credit information indicate adequate payment capacity regarding the amount and origin of the debtors' income to meet the required payments.
- Acceptable (Acc): The credits classified in this category are acceptably served and protected, but some weaknesses could potentially affect, temporarily or permanently, the debtor's payment capacity or the underlying project's cash flows in such a way that, if not corrected promptly, they would affect the normal collection of the credit or contract.
- Deficient (Def): Credits or contracts in this category present deficiencies in the debtor's payment capacity or the project's cash flows, compromising the regular collection of the obligation in the agreed terms.
- Difficult to collect (Diff): A loan with the characteristics of a deficient loan, but to a greater extent, such that the probability of collection is highly doubtful.
- Irrecoverable (Irr): This is a loan that is estimated to be uncollectible.

For our purposes, any credit beyond Normal is considered risky. Thus, the credit risk index (CRI) is the ratio of risky credits to the total credits and our variable of interest:

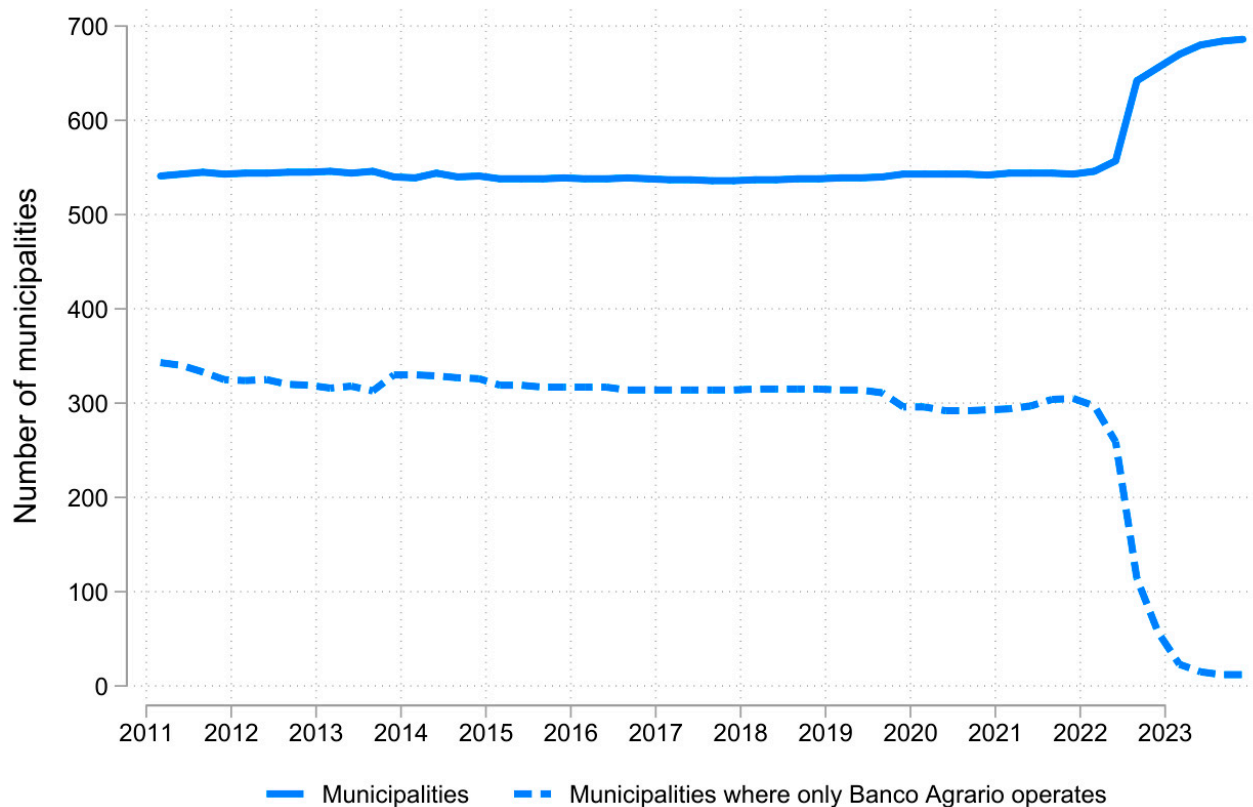
$$CRI : \frac{Acc + Def + Diff + Irr}{Total Credits}$$

This index measures the proportion of the credit institutions' loan portfolio in a risky collection condition. In addition to financial information, the CFS data contains information on the number of offices and employees the credit entity has in each municipality for each quarter. Which we use as control variables in some of our estimations.

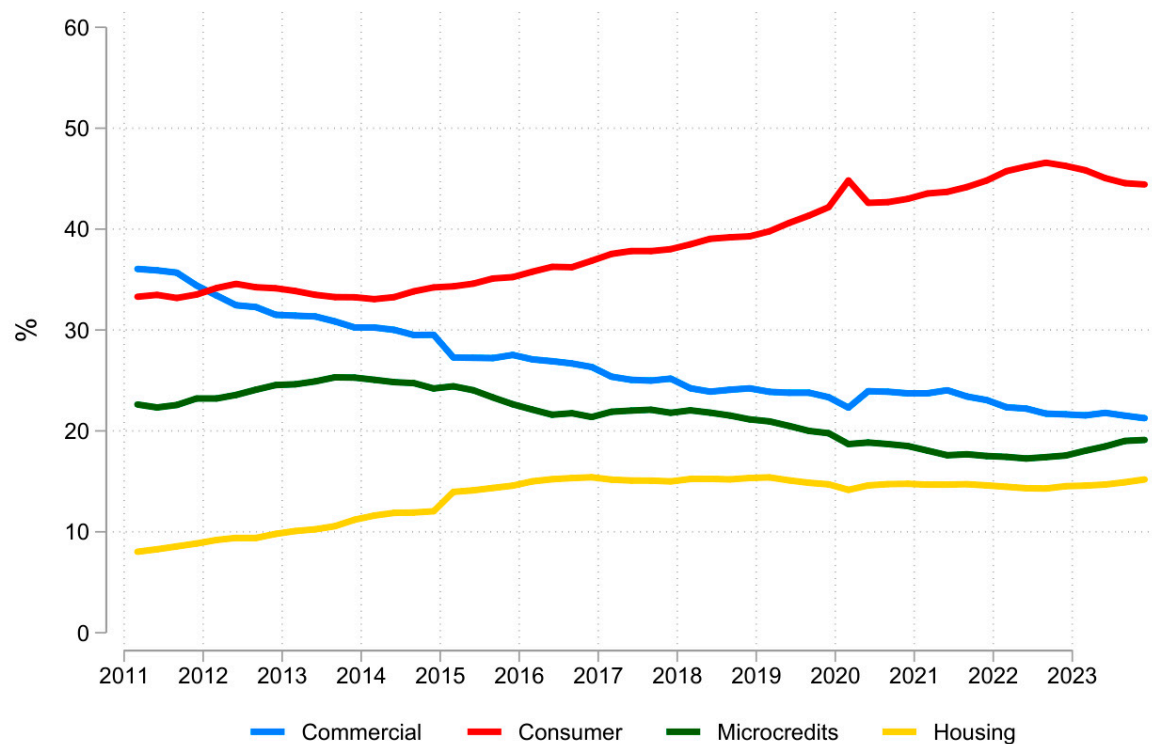
In this paper, we are interested in analyzing the case of small municipalities in Colombia. To do so, we define small municipalities as those with less than 200 thousand inhabitants and located more than 50 km in linear distance from a capital city. These two criteria allow us to consider municipalities whose markets are not substantially influenced by large cities and whose populations tend to be predominantly rural. In Figure 1, we present the number of small municipalities in our database and those in which Banco Agrario is the only credit institution operating. The number of small municipalities stays the same until 2021, between 530 and 550, and grows to 700 by 2022–2023. Banco Agrario is the only remaining government-owned commercial bank focused on the rural sector, and even now, it is the only bank operating in a sizable number of poorly connected municipalities. Regarding the municipalities where Banco Agrario is a monopoly, this has decreased over the years, going from just over 350 in 2011 to just over 300 in 2021, and close to 0 by 2023. In 2022, the Decree 1459, whose purpose was to modernize the financial system, eased the operation of banking correspondents changing the competitive landscape of small rural municipalities. Our database also includes DANE (National Statistical Department) information on municipal added value and population to measure the average income per inhabitant per municipality and year. DANE data is available for 2011–2023, our analysis period.

In Figure 2, we present the participation by credit types of credit institutions operating in small municipalities. To do this, we add the balances of each type of credit for all the small municipalities, estimating the total participation of each type of portfolio. For the first years of our sample, the primary type was the commercial one; however, since 2012, consumer credit has become the dominant type for small municipalities. Microcredit loans are in third place, while housing credit is the lowest. Since we are dealing with small

municipalities, their economies are small and probably do not have a sizable demand for housing loans; consequently, we removed this category from our analysis.

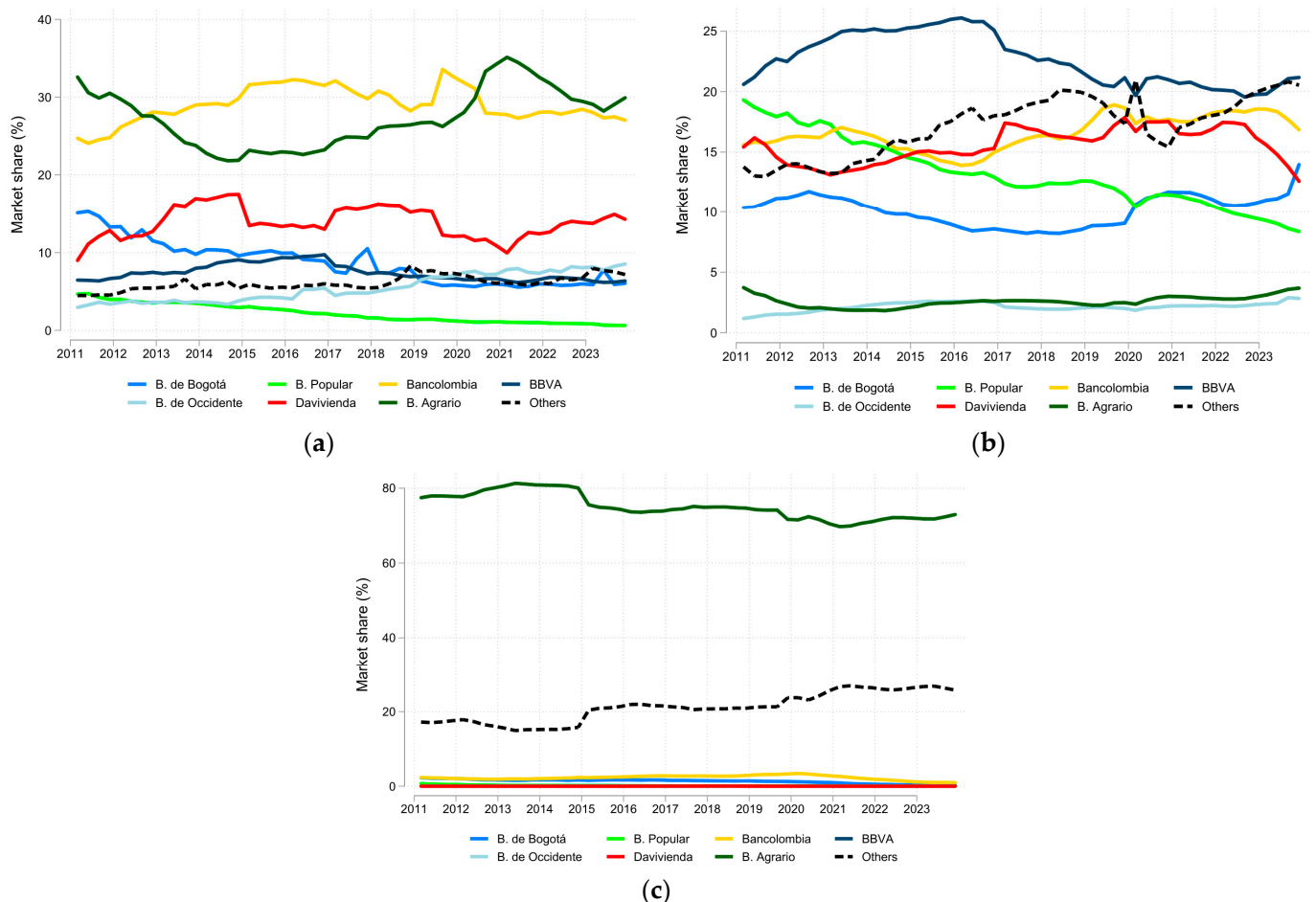


**Figure 1.** Number of municipalities more than 50 km from a capital city and with less than 200 thousand inhabitants.



**Figure 2.** Market share by credit type.

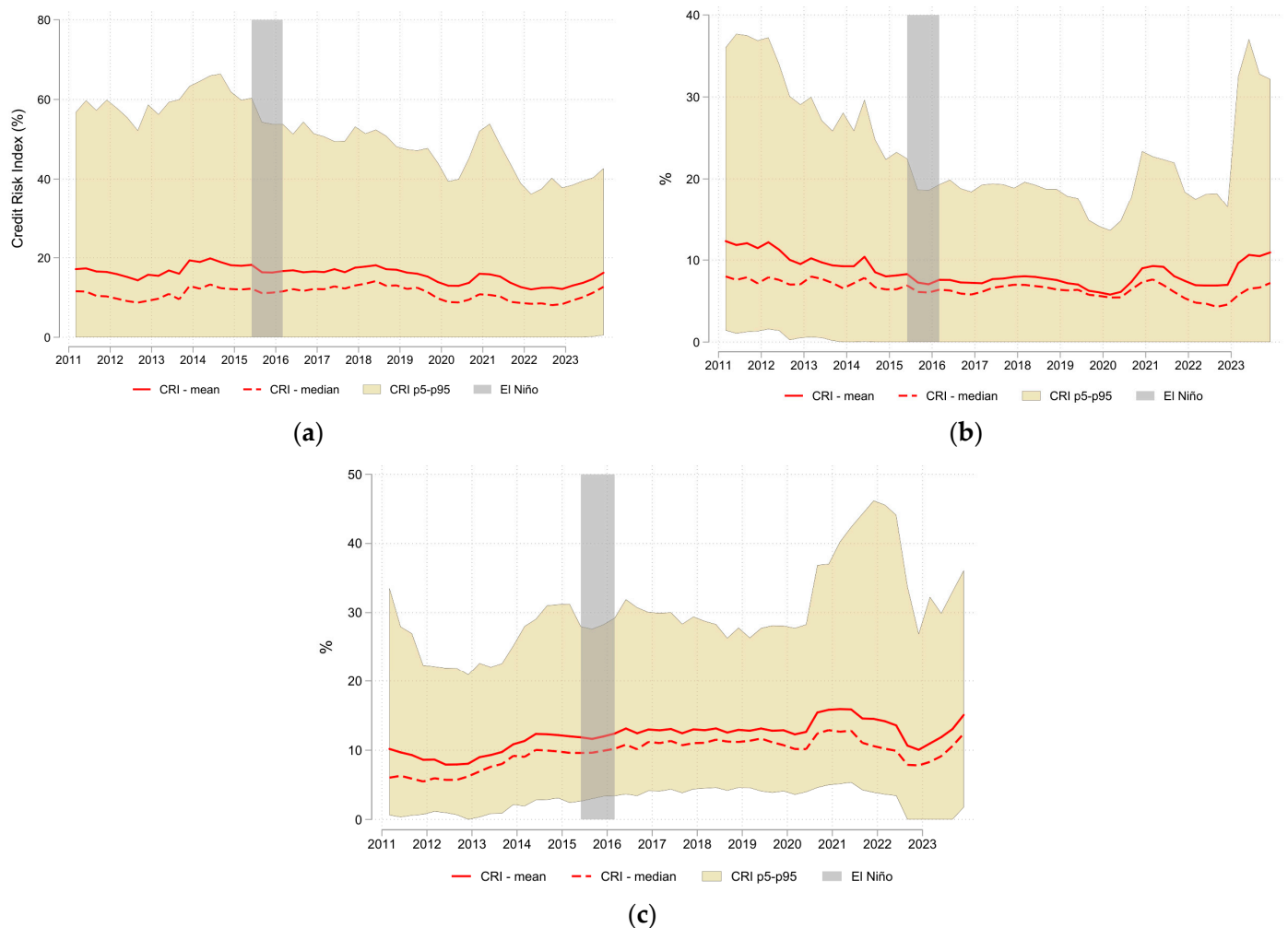
In Figure 3, we present the market share of the leading credit institutions for the three credit types. For each type of credit, we aggregate the balances of the entities in all small municipalities and calculate the share. Major credit institutions in the country, including Banco de Bogotá, Banco Popular, Bancolombia, BBVA, Banco de Occidente, Davivienda, and Banco Agrario, are the key players. Banco Agrario stands out as the dominant force in the microcredit type, holding a significant 80% share of the entire credit type. However, its dominance is on a downward trend due to the entry of new credit institutions. In the commercial credit type, Banco Agrario and Bancolombia share the dominance, representing around 60% during the entire study period. In consumer credit, Banco Agrario has a low participation rate; this credit type does not present a strong concentration phenomenon like the other credit types; therefore, no dominant entity stands out in this credit type.



**Figure 3.** Participation of the leading credit institutions by credit type. (a) Commercial. (b) Consumer. (c) Microcredits.

In Figure 4, we present the distribution of the CRI at the municipality-credit institution level for each credit type through the quarters. We show the values corresponding to the average, the median, and the 95th and 5th percentiles. Additionally, we present a gray bar that represents the presence of El Niño phenomenon, according to the Oceanic Niño Index (ONI). The CRI associated with the microcredit credit type has experienced an increase over time. Regarding the consumer credit CRI, these have experienced a slight downward trend, on average, and substantially for the 95th percentile, that is, the consumer credit type has experienced a tendency to be less risky over time. Commercial credit is the riskiest of all credit types, having the highest average levels along with the highest values for the 95th percentile. CRIs for all credit types have experienced an upward jump since 2020, likely

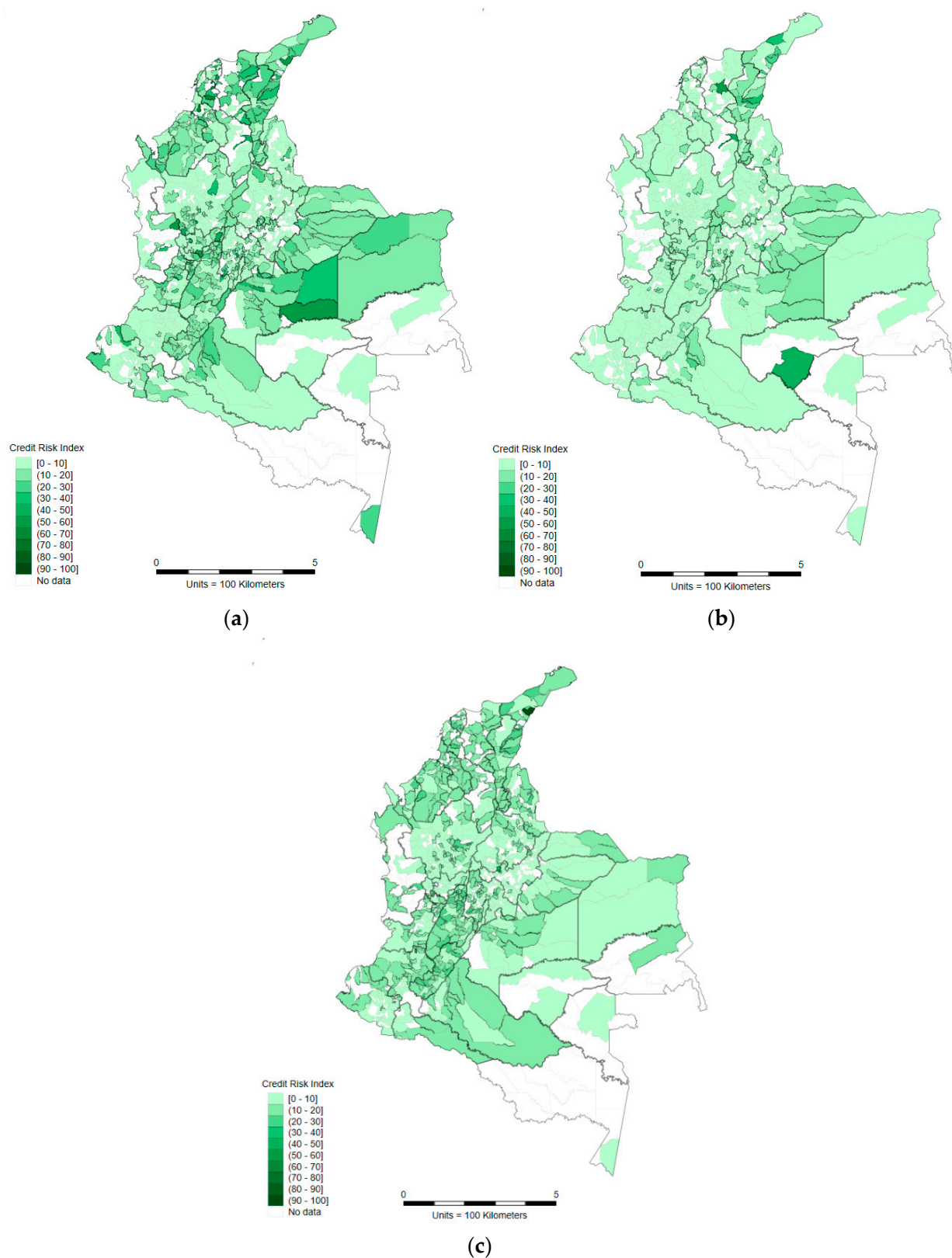
due to the COVID-19 pandemic. Finally, CRI does not seem to respond to the presence of El Niño.



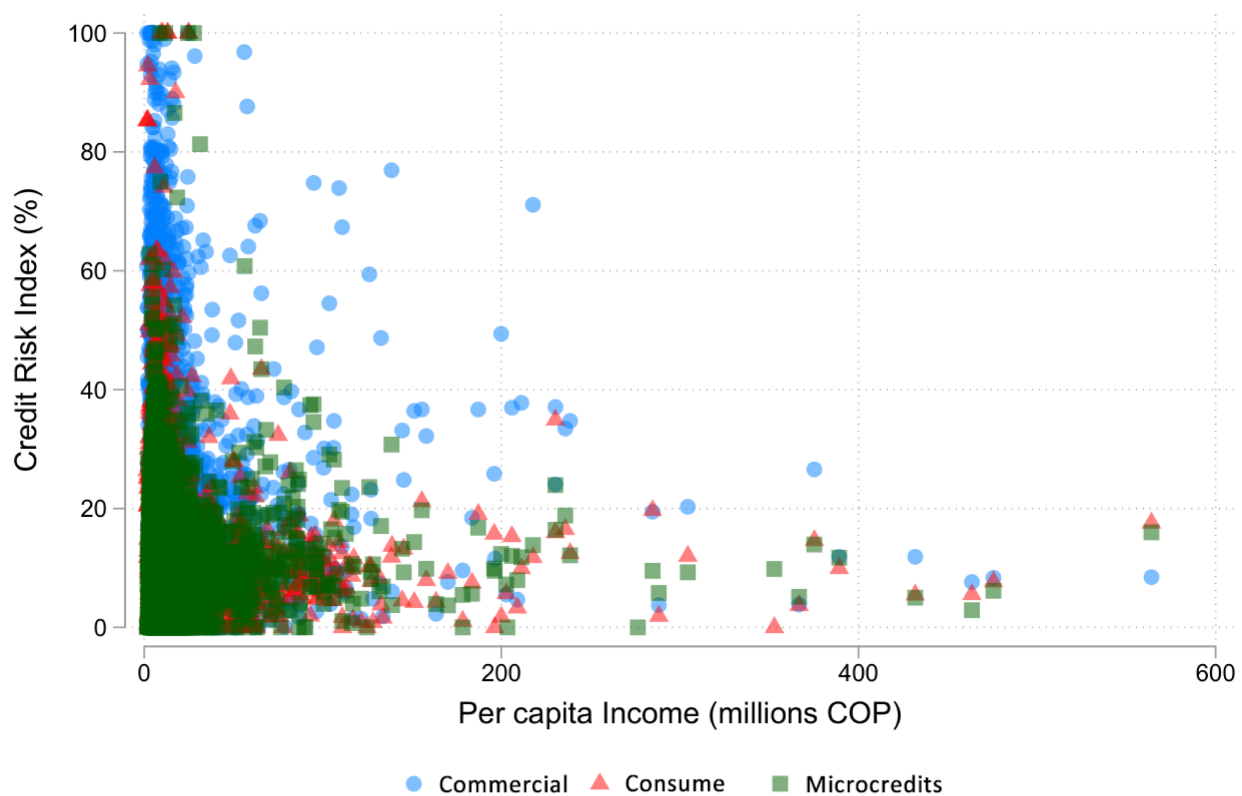
**Figure 4.** Credit risk index. (a) Commercial. (b) Consumer. (c) Microcredits.

In Figure 5, we show maps with the geographic distribution at the municipal level of the average CRI in 2023 for each credit type. We define 11 categories to classify the CRI; we split the interval 0–100 into 10 equal parts; lighter shades represent lower CRI levels, and darker shades represent higher CRI levels. Consumer credit has the lowest average CRI level among the country's different municipalities. In contrast, in the commercial type, there is a large group of municipalities with a high CRI greater than 10%. Municipalities with a CRI greater than 10 are dispersed throughout the country.

Finally, in Figure 6, we present a dispersion map between the average annual CRI for each credit type in each municipality and our measure of average income per capita. As expected, small municipalities with higher average income per capita tend to have lower CRIs for all credit types. The inverse relationship is lower for the commercial credit type. The reason is that commercial credits are, on average, riskier, as evidenced by the figures above.



**Figure 5.** Credit risk map by municipality, for the year 2023. (a) Commercial. (b) Consumer. (c) Microcredits.



**Figure 6.** Credit risk index vs. per capita income.

### 3.2. Climate Data

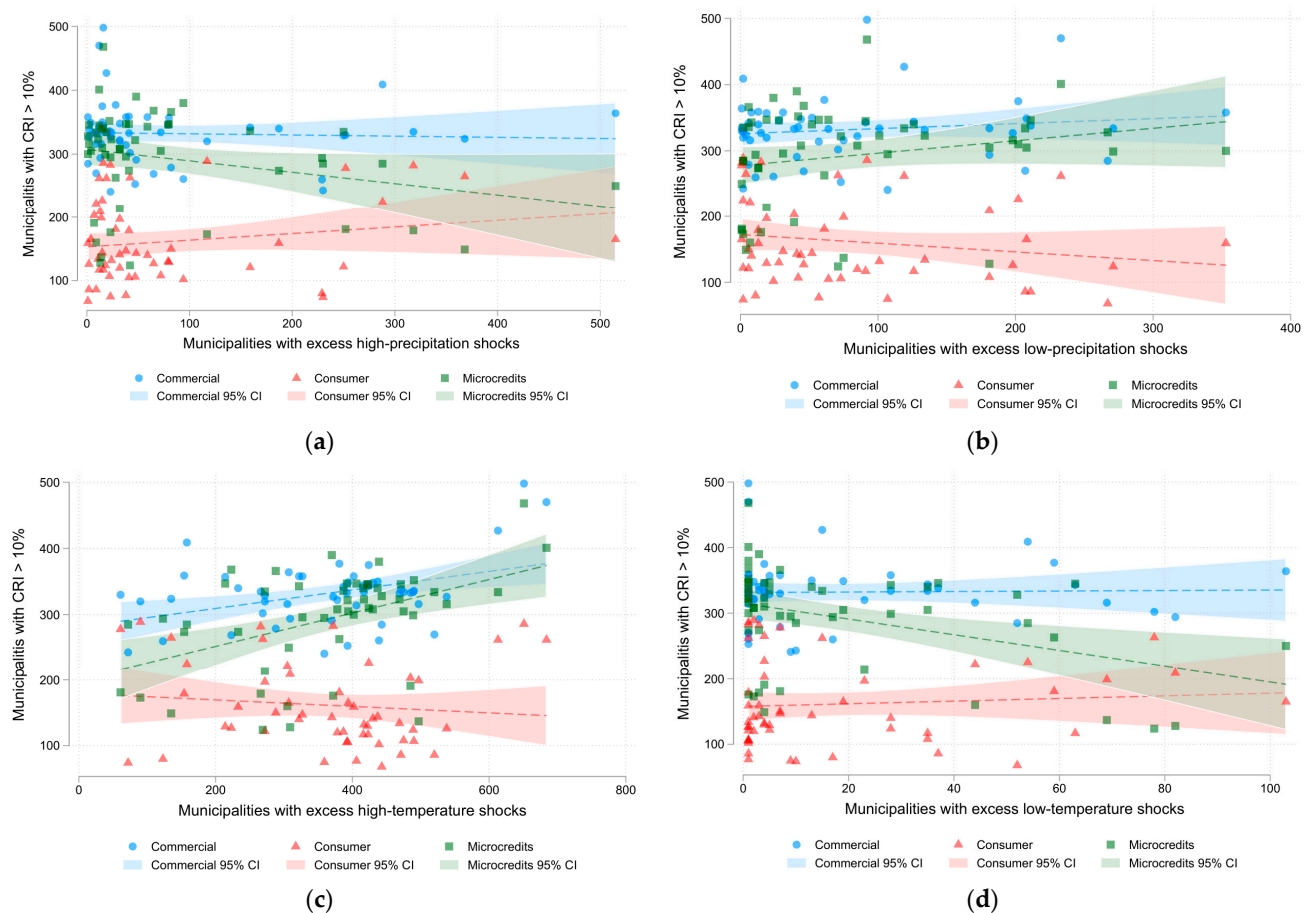
Regarding climate information, we use CHIRPS for precipitation data and Copernicus for minimum and maximum temperature data. We take climate information for each municipality daily from 1981 to 2023. The Copernicus data, publicly provided by the European Centre for Medium-Range Weather Forecasts, have information at the 30 km grid level. The CHIRPS data are at a 5 km grid level and allow precipitation measurements in mm per grid. From the shapefiles for Colombia, climate data can be added at the municipality level daily from 1981 to 2023.

We calculate the quarterly accumulated precipitation and define shocks as events in which the quarterly precipitation was above the 90th or below the 10th percentile in the 1981–2010 historical percentile for each calendar quarter. For temperature, we define shocks as the event in which the day's maximum temperature was above the 90th percentile of the historical data or when the minimum temperature was below the 10th percentile for each calendar quarter.

We use the period 1981–2010 to define the thresholds to better identify weather shocks in the period for which we have financial information. Regarding the definition of the thresholds for each calendar quarter, this allows us to consider the seasonal nature of the climatic variables. Finally, we add the climatic information at a quarterly frequency. Our measures of climatic shocks are, for each municipality in each quarter of the 2011–2023 period, the quarter in which the extreme precipitation event occurred and the proportion of days in the quarter in which the extreme temperature event occurred.

As a preliminary exercise to study the relationship between the CRI and weather shocks, we present Figure 7. In this figure, we have the number of small municipalities with a CRI greater than 10% on the ordinate axis. On the abscissa axis, we have the number of municipalities with excess weather shocks during the quarter. We choose the value of 10% given that in Figure 4, we observe that entities with CRIs greater than this threshold are relatively higher than the average. When a municipality has a weather shock, we classify it

as an event in which, during the quarter, it faced temperature shocks on more than 15 days or a precipitation shock in the quarter. Therefore, we have four panels, one for each type of weather shock we define. We present a dispersion map, together with the regression line and its respective confidence interval, for each type of portfolio. The evidence found in Figure 7 shows a heterogeneous relationship between weather shocks and portfolio risk. More municipalities have CRI above 10% when excess high-precipitation shocks occur. Higher risk in the microcredit is associated with more excess high-temperature shocks. However, these high-temperature events are associated with lower levels of risk in consumer credit. A similar case occurs when more municipalities suffer low-temperature shocks, resulting in lower levels of risk in microcredit. This preliminary evidence, in the form of correlations, shows us that weather shocks influence portfolio risk.



**Figure 7.** CRI vs. weather shocks. (a) High-precipitation. (b) Low-precipitation. (c) High-temperature. (d) Low-temperature.

An alternative way to capture weather shock events from precipitation and temperature data is to calculate the Standardized Precipitation and Evapotranspiration Index or SPEI. This multi-scale drought index, proposed by Vicente-Serrano et al. (2010), identifies the onset, duration, and magnitude of drought or excess rainfall conditions in various natural systems. The SPEI considers both the precipitation deficit and the increase in atmospheric evaporation demand, which is especially dominant in periods of rainfall deficit. Its calculation requires high-quality and long-term precipitation and evaporation data, available through ground stations and gridded data based on re-analysis and satellite sets. This is precisely the data that we have. Evapotranspiration comes from temperature data following the equations of Thornthwaite (1948). We calculate the SPEI for each municipality using quarterly temperature and precipitation data. This index centers at 0. Values above

1 indicate rainy periods, greater than 1.5 indicate severe, and greater than 2 are extreme rainy periods. Values below  $-1$  indicate drought periods, lower than  $-1.5$  indicate severe drought, and lower than  $-2$  are extreme drought periods.

Figure 8 presents several series that allow us to relate the CRI with the SPEI for each quarter. The dashed line series shows the number of small municipalities with a CRI higher than 10% for each credit market. The blue area shows the number of municipalities with an SPEI greater than 1.5 in at least one month of the quarter, and the red area shows the number of municipalities with an SPEI lower than  $-1.5$  in at least one month of the quarter. We chose 1.5 since this value reflects severe weather conditions. At a glance, it is difficult to unlock any relationship. There is no evidence that CRI values change substantially during or after periods of extreme drought, such as those in 2015–2016, or severe rainfall events, such as those in 2011 and 2017.

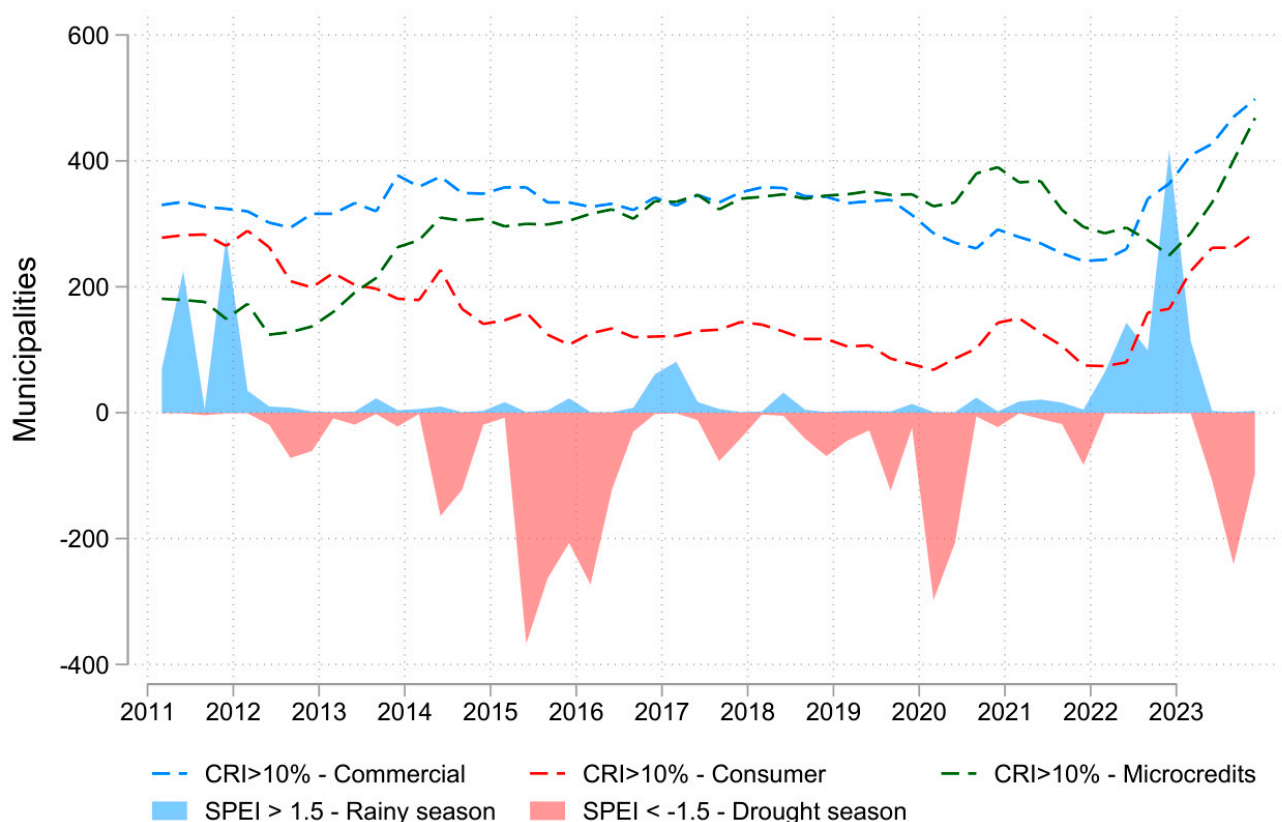


Figure 8. CRI vs. SPEI.

#### 4. Empirical Strategy

Following the theoretical results of [Adjognon et al. \(2020\)](#) and [Conning and Udry \(2007\)](#), who developed models to study the role of financial markets in rural areas of developing economies, we propose that adverse productivity shocks, such as weather shock, increase the probability of default on loans granted to farmers. Due to the negative productivity shock, the opportunity cost of repaying the loan increases; giving up current consumption to honor the debt incurred implies a lower standard of living for farmers. Therefore, farmers tend to assign a lower value to the penalty of not paying and more frequently decide not to honor their debt. Other types of shocks could lead to similar behavior by farmers, such as input price or household expenditure shocks. Additionally, the possibility of smoothing consumption through savings or agricultural insurance is very limited in rural areas of developing countries ([Cole & Xiong, 2017](#)). Together, these results imply that when weather shocks occur, the portfolio risk of banks that grant loans in these locations increases.

In this way, we study the effect that weather shocks have on the balance of portfolio at risk CRI in quarter  $t$  in municipality  $i$  for entity  $j$  by estimating the following econometric model independently for each portfolio  $k$ , with  $k = \{\text{commercial, consumer, microcredit}\}$ :

$$\ln \text{CRI}_{ijt}^k = \alpha^k \ln c_{ij,t-1}^k + \beta^k \ln v_{it} + \gamma_1^k p_{it}^{\text{high}} + \gamma_2^k p_{it}^{\text{low}} + \gamma_3^k t_{it}^{\text{high}} + \gamma_4^k t_{it}^{\text{low}} + \gamma_5^k p_{it-1}^{\text{high}} + \gamma_6^k p_{it-1}^{\text{low}} + \gamma_7^k t_{it-1}^{\text{high}} + \gamma_8^k t_{it-1}^{\text{low}} + \theta_{ij} + \theta_t + \varepsilon_{ijt} \quad (1)$$

where  $c$  is the balance of the credit portfolio of type  $k$  for intermediary  $j$  in municipality  $i$  in quarter  $t - 1$ , and  $v$  is a measure of the income per capita of municipality  $i$  in the year to which quarter  $t$  belongs. Regarding weather shocks,  $p^{\text{high}}$  is a dummy variable whose value is 1 when a quarter accumulated precipitation is above the 90th percentile of the historical data.  $t^{\text{high}}$  measures the proportion of days in the quarter when the maximum temperature is above the 90th percentile of the historical data. Similarly,  $p^{\text{low}}$  and  $t^{\text{low}}$  are 1 when the quarter accumulated precipitation and average municipality minimum temperature are below the 10th percentile of the historical data. As a robustness exercise, we worked with thresholds for the 80th and 20th percentiles.  $\theta$  are vectors of the municipality-credit institution and time-fixed effects. Finally,  $\varepsilon$  is a random error term. Equation (1) is estimated by OLS, with clusters at the municipality-credit institution level for the standard errors. Since our objective is to identify the short-run effects of climate shocks using panel data, we follow the approach proposed by Dell et al. (2014), who argue that fixed-effects panel models are particularly suitable for estimating the short-term impacts of weather and climate variability. By exploiting within-unit variation over time and controlling for time-invariant unobserved heterogeneity, this framework provides consistent estimates of the effects of temporary climatic shocks on economic outcomes.

Similarly, we use the SPEI as a measure of climatic conditions, defining shocks as the events in which the SPEI values are above or below a certain threshold. The literature proposes reasonable thresholds at  $\pm 1.5$  and  $\pm 2$ . Following the formulation of the previous equation, for the case of the SPEI, we would have the following expression:

$$\ln \text{CRI}_{ijt}^k = \alpha^k \ln c_{ij,t-1}^k + \beta^k \ln v_{it} + \gamma_1^k \text{spei}_{it}^{\text{drought}} + \gamma_2^k \text{spei}_{it}^{\text{rainy}} + \gamma_3^k \text{spei}_{it-1}^{\text{drought}} + \gamma_4^k \text{spei}_{it-1}^{\text{rainy}} + \theta_{ij} + \theta_t + \varepsilon_{ijt} \quad (2)$$

where  $\text{spei}^{\text{drought}}$  is a dummy variable, whose value is 1 when a quarter has a severe drought event ( $< -1.5$ ), and  $\text{spei}^{\text{rainy}}$  identifies a quarter with a severe rainfall event ( $> 1.5$ ). As a robustness exercise, we identify extreme drought events ( $< -2$ ) or extreme rainfall events ( $> 2$ ). Equation (2) is estimated with clusters at the municipality-credit institution level for the standard errors.

## 5. Results

### 5.1. Credit Risk and Weather Shocks

In Table 1, we present the estimation of Equation (1) using OLS. The columns present different specifications according to the type of portfolio (commercial, consumer, or microcredits) and the definition of weather shocks using the 90–10 or 80–20 percentiles of the 1981–2010 historical period, with the percentile 80–20 having more events classified as shocks. The results show that a larger portfolio is related to more at-risk loans. This result is reasonable given that an increase in the portfolio implies granting loans to some individuals with less favorable risk profiles. Interestingly, municipal branch expansion yields divergent credit risk outcomes across loan portfolios. For microcredits, increased local presence reduces at-risk balances by enhancing banks' capacity for ex-ante screening and ex-post borrower monitoring. This mechanism fails in the commercial segment, where

market-quota pressures characteristic of commercial lending likely degrade the quality of ex-ante risk assessments, resulting in higher delinquency rates. Consistently, a larger number of employees tends to increase high-risk commercial loans, but it does not hinder microcredits, since competition can encourage them to grant more loans to people with higher risk profiles. Understandably, we found evidence that the portfolio of at-risk commercial and consumer loans tends to be smaller in municipalities with higher per capita income levels. Given that these types of loans go to firms to finance their operations and people for their consumption activities, a higher income level means that they are more likely to be able to repay the loan.

**Table 1.** Risky loans and weather shocks.

|                                         | (1)                      | (2)                      | (3)                      | (4)                               | (5)                      | (6)                      |
|-----------------------------------------|--------------------------|--------------------------|--------------------------|-----------------------------------|--------------------------|--------------------------|
|                                         | Shocks at<br>90% and 10% | Shocks at<br>80% and 20% | Shocks at<br>90% and 10% | Shocks at<br>80% and 20%          | Shocks at<br>90% and 10% | Shocks at<br>80% and 20% |
| Dep. Var.: Portfolio at<br>Risk in Logs | Commercial               |                          | Consumer                 |                                   | Microcredits             |                          |
| Portfolio balance in logs               | 0.594 ***<br>(0.0238)    | 0.594 ***<br>(0.0238)    | 0.774 ***<br>(0.0217)    | 0.774 ***<br>(0.0217)             | 0.874 ***<br>(0.0232)    | 0.874 ***<br>(0.0231)    |
| Number of offices                       | 0.149 *<br>(0.0765)      | 0.148 *<br>(0.0766)      | −0.00961<br>(0.0296)     | −0.0100<br>(0.0296)               | −0.123 **<br>(0.0495)    | −0.122 **<br>(0.0495)    |
| Number of employees                     | 0.00222 **<br>(0.00105)  | 0.00223 **<br>(0.00105)  | −0.000579<br>(0.00231)   | −0.000587<br>(0.00231)            | 0.00218<br>(0.00137)     | 0.00217<br>(0.00138)     |
| Per capita income in<br>logs            | −0.171 **<br>(0.0727)    | −0.172 **<br>(0.0726)    | −0.190 ***<br>(0.0714)   | −0.188 ***<br>(0.0716)            | −0.0716<br>(0.0451)      | −0.0724<br>(0.0451)      |
| Low-precipitation shock                 | 0.0145<br>(0.0155)       | 0.0208<br>(0.0128)       | −0.00519<br>(0.0134)     | 0.00208<br>(0.0107)               | 0.0162 *<br>(0.00859)    | 0.0161 **<br>(0.00772)   |
| High-precipitation<br>shock             | 0.0141<br>(0.0161)       | 0.00748<br>(0.0140)      | 0.00461<br>(0.0130)      | $7.40 \times 10^{-5}$<br>(0.0118) | −0.000845<br>(0.00935)   | −0.00308<br>(0.00848)    |
| Low-temperature shock                   | 0.229<br>(0.180)         | 0.100<br>(0.127)         | 0.512 ***<br>(0.140)     | 0.340 ***<br>(0.105)              | 0.119<br>(0.112)         | −0.00306<br>(0.0801)     |
| High-temperature<br>shock               | −0.0476<br>(0.0513)      | −0.0626<br>(0.0504)      | −0.0137<br>(0.0430)      | −0.0413<br>(0.0398)               | 0.0181<br>(0.0320)       | −0.0119<br>(0.0296)      |
| Low-precipitation shock<br>(t − 1)      | 0.000567<br>(0.0151)     | 0.0148<br>(0.0129)       | −0.0228<br>(0.0142)      | −0.00921<br>(0.0111)              | 0.0130<br>(0.00898)      | 0.0152 **<br>(0.00772)   |
| High-precipitation<br>shock (t − 1)     | 0.0154<br>(0.0157)       | 0.00741<br>(0.0138)      | 0.00513<br>(0.0128)      | −0.00130<br>(0.0114)              | −0.00317<br>(0.00964)    | 0.00479<br>(0.00841)     |
| Low-temperature shock<br>(t − 1)        | 0.102<br>(0.170)         | 0.128<br>(0.117)         | 0.597 ***<br>(0.143)     | 0.486 ***<br>(0.102)              | −0.0160<br>(0.103)       | −0.0102<br>(0.0736)      |
| High-temperature<br>shock (t − 1)       | −0.0671<br>(0.0517)      | −0.0665<br>(0.0479)      | 0.0229<br>(0.0463)       | 0.0123<br>(0.0425)                | −0.0381<br>(0.0342)      | −0.0506<br>(0.0318)      |
| Observations                            | 51,260                   | 51,260                   | 49,402                   | 49,402                            | 48,462                   | 48,462                   |
| R-squared                               | 0.774                    | 0.774                    | 0.890                    | 0.890                             | 0.885                    | 0.885                    |

Note: Standard errors with cluster at the municipality-entity level are in parentheses. All regressions include time and municipality-entity fixed effects. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Regarding weather shocks, there is evidence that they tend to increase risky loans in the consumer and microcredit segments. Low-temperature shocks, both contemporaneous and lagged, increase risky commercial loans in both sets of percentiles. For microcredits, low-precipitation contemporaneous shocks increase risk in both set of percentiles, with the lagged shocks also affecting the 80th–20th percentile (the definition that yields more weather shocks). Table A1, in the Appendix A, depicts similar tests, with an alternative

definition of risky loans as a robustness analysis. In that case we define  $CRI_A$  as the ratio of risky credits, except Normal and Acceptable, to the total credits and our variable of interest:

$$CRI_A : \frac{Def + Diff + Irr}{Total\ Credits}$$

The results of this alternative analysis are qualitatively similar to those presented in Table 1, except they are stronger. Consumer credits are also negatively affected by lagged low-temperature shocks, similarly microcredits are not negatively affected by high temperature shocks. Interestingly, the negative impact of low precipitation shocks is stronger for microcredits.

A relevant question to study is how these results differ when credit applicants face a smaller range of options, which may affect how supply responds to weather shocks. In this case, we focus only on municipalities where Banco Agrario is a monopoly, reestimating Equation (1). In Table 2, we present the estimation results of Equation (1) using only data from municipalities where Banco Agrario is the only supplier. This condition no longer applies for the period 2022–2023 (see Figure 1); thus, our tests only cover the period 2011–2021. The columns present different specifications depending on the type of portfolio (commercial, consumer, or micro-credit) and the definition of weather shocks using the 90–10 or 80–20 percentiles of the 1981–2010 historical data.

The results for portfolio size and number of offices are very similar to those in Table 1. A larger portfolio size is associated with a higher volume of credits at risk across the three segments, while a higher number of offices increases the risk of commercial and consumer (an effect absent in Table 1) loans but reduces the risk in the microcredit portfolio. This result, now associated with municipalities where only Banco Agrario operates, albeit with smaller coefficients, replicates the impact we saw in the large sample: offices granting more credit to firms and individuals with riskier credit profiles. Regarding weather shocks, for Banco Agrario loans, the shock that increases risk is a low-temperature one, both contemporaneous and lagged, across all segments, except for the lagged shock under the more extreme definition (90–10 percentile) for commercial loans. While effects on the commercial segment were absent in the large sample, they appear strong and consistent in the Banco Agrario sample, likely due to a more homogeneous set of customers. Low-precipitation shocks' impact on the microcredit segment, affecting the whole sample, disappears in this sample, with a marginal effect on commercial loans under the relaxed definition of shocks. Additionally, we find that a lagged high-temperature shock reduces the risk of the micro-credit portfolio, a spurious result surely coming from the extremely complex dynamics that characterize the relationship between weather and credit behavior.

Finally, we address the estimation of the alternative specification we defined in Equation (2), where we relate loan risk with shock measures from the SPEI. Table 3 presents the results of estimating Equation (2) using OLS. The columns present different specifications according to the type of portfolio (commercial, consumer, or microcredits) and the definition of weather shocks using the SPEI thresholds of  $+/-1.5$  (severe shock) and  $+/-2$  (extreme shock). The results for the control variables are similar to Table 1. A direct relationship exists between loans at risk and portfolio volume for all segments. For commercial portfolios the number of offices and employees yield similar higher levels of risk, while per capita income reduces credit risk. For the consumer segment the only significant effect is the negative impact of per capita income. For microcredit portfolios, loans at risk decrease with more branches. However, we find striking differences in weather shocks. Our findings indicate that severe rainfall shocks increase commercial loan risk, while consumer loans remain unaffected. In contrast, microcredit portfolios are sensitive to both drought and precipitation shocks. Specifically, microcredit risk increases with contemporaneous severe

and lagged extreme drought shocks, alongside lagged severe and extreme rainy shocks. The evidence indicates that drought shocks increase the microcredit portfolio at risk. Given the difference in nature of both weather shock measures, the results are unsurprising, which compels credit institutions to consider alternative and complementary measures to assess the impact of extreme weather on their non-performing loans.

**Table 2.** Risky loans and weather shocks: Municipalities where Banco Agrario is a monopoly (2011–2021).

|                                         | (1)                      | (2)                      | (3)                      | (4)                      | (5)                      | (6)                      |
|-----------------------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
|                                         | Shocks at<br>90% and 10% | Shocks at<br>80% and 20% | Shocks at<br>90% and 10% | Shocks at<br>80% and 20% | Shocks at<br>90% and 10% | Shocks at<br>80% and 20% |
| Dep. Var.: Portfolio at<br>Risk in Logs | Commercial               |                          | Consumer                 |                          | Microcredits             |                          |
| Portfolio balance in logs               | 0.568 ***<br>(0.0542)    | 0.569 ***<br>(0.0541)    | 0.624 ***<br>(0.0469)    | 0.626 ***<br>(0.0470)    | 1.081 ***<br>(0.0712)    | 1.084 ***<br>(0.0714)    |
| Number of offices                       | 1.017 ***<br>(0.0670)    | 1.011 ***<br>(0.0671)    | 0.148 **<br>(0.0701)     | 0.158 **<br>(0.0710)     | −0.137 ***<br>(0.0310)   | −0.121 ***<br>(0.0307)   |
| Number of employees                     | −0.00924<br>(0.0185)     | −0.00897<br>(0.0185)     | −0.0158<br>(0.0225)      | −0.0154<br>(0.0225)      | 0.0108<br>(0.00883)      | 0.0102<br>(0.00887)      |
| Per capita income in<br>logs            | 0.0768<br>(0.132)        | 0.0830<br>(0.131)        | 0.0643<br>(0.120)        | 0.0707<br>(0.120)        | −0.0211<br>(0.0625)      | −0.0204<br>(0.0623)      |
| Low-precipitation shock                 | 0.00738<br>(0.0303)      | 0.0336<br>(0.0244)       | 0.0468<br>(0.0316)       | 0.0502 *<br>(0.0281)     | 0.0150<br>(0.0115)       | 0.0157<br>(0.0104)       |
| High-precipitation<br>shock             | 0.0185<br>(0.0320)       | 0.0266<br>(0.0278)       | −0.0214<br>(0.0394)      | −0.00123<br>(0.0348)     | −0.0182<br>(0.0180)      | −0.0150<br>(0.0133)      |
| Low-temperature shock                   | 1.094 ***<br>(0.380)     | 0.900 ***<br>(0.265)     | 0.995 ***<br>(0.356)     | 0.741 ***<br>(0.248)     | 0.648 ***<br>(0.166)     | 0.402 ***<br>(0.121)     |
| High-temperature<br>shock               | −0.0877<br>(0.0982)      | −0.0488<br>(0.0898)      | 0.120<br>(0.113)         | 0.0423<br>(0.104)        | −0.0243<br>(0.0454)      | −0.0498<br>(0.0430)      |
| Low-precipitation shock<br>(t − 1)      | −0.0260<br>(0.0284)      | 0.0192<br>(0.0238)       | −0.0138<br>(0.0351)      | −0.0153<br>(0.0279)      | 0.0115<br>(0.0114)       | 0.00797<br>(0.0106)      |
| High-precipitation<br>shock (t − 1)     | 0.0308<br>(0.0328)       | 0.0414<br>(0.0256)       | 0.0197<br>(0.0398)       | 0.0294<br>(0.0296)       | −0.0173<br>(0.0176)      | −0.0205<br>(0.0126)      |
| Low-temperature shock<br>(t − 1)        | 0.520<br>(0.359)         | 0.488 **<br>(0.222)      | 1.028 ***<br>(0.364)     | 0.845 ***<br>(0.245)     | 0.405 ***<br>(0.151)     | 0.200 *<br>(0.102)       |
| High-temperature<br>shock (t − 1)       | 0.0532<br>(0.105)        | 0.0485<br>(0.0990)       | 0.0710<br>(0.118)        | 0.0474<br>(0.105)        | −0.0719<br>(0.0534)      | −0.115 **<br>(0.0522)    |
| Observations                            | 11,818                   | 11,818                   | 10,261                   | 10,261                   | 13,526                   | 13,526                   |
| R-squared                               | 0.724                    | 0.724                    | 0.478                    | 0.478                    | 0.876                    | 0.876                    |

Note: Standard errors with cluster at the municipality-entity level are in parentheses. All regressions include time and municipality-entity fixed effects. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

In summary, the evidence obtained from Tables 1–3 shows that low-temperature and low-precipitation combined with high-temperature shocks tend to be associated with increases in the portfolio at risk. Low-precipitation and high-temperature shocks are associated with drought events and an increase in the risk of the microcredit portfolio. The SPEI measure also provides evidence of the harmful effects of rainy shocks. The harmful effects on crops (diseases and crop losses) and human health (diseases and lower worker productivity) of low temperatures and droughts (Meierrieks, 2021; Cohen et al., 2021; Liliane & Charles, 2020; Thakur et al., 2010) explain this relationship. Thus, these weather events can result in a negative shock to individuals' incomes. On the other hand, an income reduction can motivate an increase in the demand for credit as a consumption-smoothing mechanism (Colarieti et al., 2024; Bunn et al., 2018), or encourage additional investment in agricultural inputs by affected farmers to cope with the adverse effects of the shocks

(Moahid et al., 2023); in this way access to credit plays a significant role in mitigating the negative impact of weather shocks (Nguyen et al., 2023).

**Table 3.** Risky loans and SPEI.

|                                         | (1)                     | (2)                     | (3)                    | (4)                    | (5)                   | (6)                   |
|-----------------------------------------|-------------------------|-------------------------|------------------------|------------------------|-----------------------|-----------------------|
|                                         | Shocks at<br>+/-1.5     | Shocks at<br>+/-2       | Shocks at<br>+/-1.5    | Shocks at<br>+/-2      | Shocks at<br>+/-1.5   | Shocks at<br>+/-2     |
| Dep. Var.: Portfolio at<br>Risk in Logs | Commercial              |                         | Consumer               |                        | Microcredits          |                       |
| Portfolio balance in logs               | 0.594 ***<br>(0.0238)   | 0.594 ***<br>(0.0238)   | 0.773 ***<br>(0.0217)  | 0.773 ***<br>(0.0217)  | 0.874 ***<br>(0.0231) | 0.874 ***<br>(0.0231) |
| Number of offices                       | 0.149 *<br>(0.0764)     | 0.149 *<br>(0.0764)     | -0.00726<br>(0.0296)   | -0.00801<br>(0.0297)   | -0.122 **<br>(0.0494) | -0.122 **<br>(0.0495) |
| Number of employees                     | 0.00221 **<br>(0.00105) | 0.00222 **<br>(0.00105) | -0.000606<br>(0.00229) | -0.000594<br>(0.00230) | 0.00217<br>(0.00137)  | 0.00217<br>(0.00137)  |
| Per capita income in<br>logs            | -0.172 **<br>(0.0726)   | -0.173 **<br>(0.0726)   | -0.193 ***<br>(0.0711) | -0.194 ***<br>(0.0711) | -0.0715<br>(0.0451)   | -0.0725<br>(0.0451)   |
| SPEI Drought                            | -0.00220<br>(0.0162)    | -0.0123<br>(0.0266)     | -0.00448<br>(0.0144)   | -0.0272<br>(0.0251)    | 0.0157 *<br>(0.00943) | 0.0256<br>(0.0159)    |
| SPEI Rainy                              | 0.0178<br>(0.0208)      | 0.0914 **<br>(0.0357)   | 0.0156<br>(0.0187)     | 0.0123<br>(0.0341)     | 0.0205<br>(0.0133)    | 0.0274<br>(0.0264)    |
| SPEI Drought (t - 1)                    | -0.0159<br>(0.0157)     | -0.0147<br>(0.0271)     | 0.000133<br>(0.0146)   | 0.00181<br>(0.0243)    | 0.0112<br>(0.00993)   | 0.0315 *<br>(0.0166)  |
| SPEI Rainy (t - 1)                      | 0.0165<br>(0.0215)      | 0.0411<br>(0.0378)      | 0.0213<br>(0.0174)     | 0.0306<br>(0.0319)     | 0.0264 *<br>(0.0139)  | 0.0479 **<br>(0.0242) |
| Observations                            | 51,260                  | 51,260                  | 49,402                 | 49,402                 | 48,462                | 48,462                |
| R-squared                               | 0.774                   | 0.774                   | 0.890                  | 0.890                  | 0.885                 | 0.885                 |

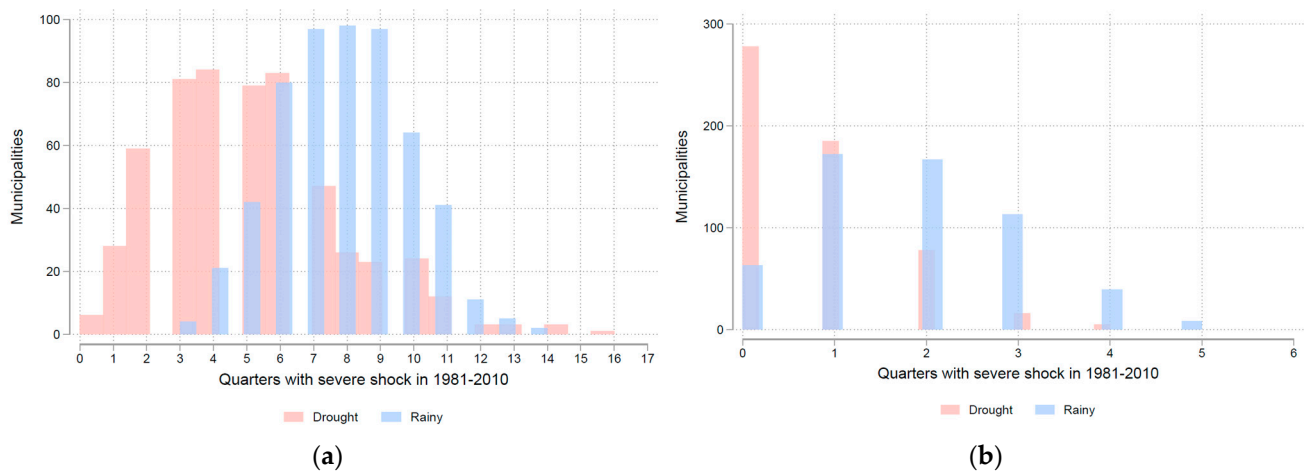
Note: Standard errors with cluster at the municipality-entity level are in parentheses. All regressions include time and municipality-entity fixed effects. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## 5.2. Controlling for Exposition to Previous SPEI-Shocks

There is a potential problem with the results in Tables 1–3, with some credit applicants adapting or coping more easily with an extreme weather event. These applicants may live in areas where these events are persistent and may have developed skills so that these events do not result in default. Thus, an unobservable component may bias the estimated coefficients downwards, given that an absence of risk reaction to a weather event may be because, in that municipality, there is greater adaptability to shocks relative to other municipalities. To overcome this problem, we use data from 1981 to 2010 to calculate the number of quarters with weather shocks measured with SPEI. In Figure 9, we present two histograms with the distribution of the number of quarters with SPEI-shocks in 1981–2010 by municipality, according to the type of shock: severe or extreme. The municipalities in our sample tend to be exposed to rain shocks to a greater extent, with drought shocks being the least frequent. Regarding severe shocks, the mode tends to be 8 quarters for rain and 4 for drought, whereas with extreme shocks, the mode is zero quarters for drought and 1 for rain.

Table 4 presents the results of controlling for the potential bias associated with prior exposure to shocks for the microcredit segment. This table is similar to specifications 5 and 6 of Table 3 except it incorporates an interaction of the variable of rainfall or drought shock according to SPEI with a variable that measures the degree of prior exposure of the municipality to that type of shock, as depicted in Figure 9. For example, this shows the severe drought shocks and the interaction between these types of shocks and the municipality's prior exposure to severe drought shocks. Since prior exposure to the shock would vary across municipalities but not over time, it is absorbed by the municipality's fixed effects in Table 3. Thus, given that the functional form associated with Table 3 does not allow the evaluation of the effect of previous exposure to shocks, we devised Table 4. Interestingly and reassuring, no interaction term is significant in the specifications 1 to 4. However, there is evidence that for microcredits some resilience develops when suffering a prior SPEI rainy severe shock. In

general, we find that prior exposure to climate shocks does not play a role in how they affect portfolio risk, except for the discussed microcredit case.



**Figure 9.** Exposition to previous SPEI-shocks. (a) Severe shocks ( $|\text{SPEI}| > 1.5$ ). (b) Extreme shocks ( $|\text{SPEI}| > 2$ ).

**Table 4.** Risky loans and SPEI: Exposition to previous SPEI-shocks.

| Dep. Var.: Portfolio at Risk in Logs                         | (5)                     | (6)                   |
|--------------------------------------------------------------|-------------------------|-----------------------|
|                                                              | Shocks at<br>+/- 1.5    | Shocks at<br>+/- 2    |
|                                                              | Microcredits            |                       |
| Portfolio balance in logs                                    | 0.874 ***<br>(0.0231)   | 0.874 ***<br>(0.0231) |
| Number of offices                                            | −0.122 **<br>(0.0493)   | −0.122 **<br>(0.0495) |
| Number of employees                                          | 0.00216<br>(0.00137)    | 0.00218<br>(0.00137)  |
| Per capita income in logs                                    | −0.0706<br>(0.0451)     | −0.0723<br>(0.0451)   |
| SPEI Drought                                                 | 0.0134<br>(0.0177)      | 0.0159<br>(0.0195)    |
| SPEI Drought × Exposition to previous<br>SPEI-shocks         | 0.000480<br>(0.00388)   | 0.0198<br>(0.0198)    |
| SPEI Rainy                                                   | 0.0613<br>(0.0483)      | 0.0171<br>(0.0364)    |
| SPEI Rainy × Exposition to previous<br>SPEI-shocks           | −0.00647<br>(0.00748)   | 0.00856<br>(0.0207)   |
| SPEI Drought (t − 1)                                         | 0.00429<br>(0.0187)     | 0.0247<br>(0.0212)    |
| SPEI Drought (t − 1) × Exposition to previous<br>SPEI-shocks | 0.00166<br>(0.00429)    | 0.0135<br>(0.0207)    |
| SPEI Rainy (t − 1)                                           | 0.0905 **<br>(0.0414)   | 0.0372<br>(0.0346)    |
| SPEI Rainy (t − 1) × Exposition to previous<br>SPEI-shocks   | −0.00994 *<br>(0.00587) | 0.00873<br>(0.0206)   |
| Observations                                                 | 48,462                  | 48,462                |
| R-squared                                                    | 0.885                   | 0.885                 |

Note: Standard errors with cluster at the municipality-entity level are in parentheses. All regressions include time and municipality-entity fixed effects. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

### 5.3. The Role of Distance in the Heterogeneity of Effects

Table 5 presents a concept similar to that depicted in Table 4, this time with weather shocks interacting with the distance to the nearest market. The logic here is that municipalities further from their natural market can suffer stronger effects from weather shocks. The results show that indeed isolated municipalities have stronger effects when suffering from weather shocks, with distance factoring in for rainy shocks for commercial loans and microcredit and for lagged droughts in consumer credits.

**Table 5.** Risky loans and SPEI: Distance to nearest market.

|                                                         | (1)                                    | (2)                                    | (3)                      | (4)                      | (5)                                    | (6)                     |
|---------------------------------------------------------|----------------------------------------|----------------------------------------|--------------------------|--------------------------|----------------------------------------|-------------------------|
|                                                         | Shocks at<br>+/-1.5                    | Shocks at<br>+/-2                      | Shocks at<br>+/-1.5      | Shocks at<br>+/-2        | Shocks at<br>+/-1.5                    | Shocks at<br>+/-2       |
| Dep. Var.: Portfolio at<br>Risk in Logs                 | Commercial                             |                                        | Consumer                 |                          | Microcredits                           |                         |
| Portfolio balance in logs                               | 0.538 ***<br>(0.0268)                  | 0.538 ***<br>(0.0268)                  | 0.804 ***<br>(0.0241)    | 0.804 ***<br>(0.0241)    | 0.880 ***<br>(0.0308)                  | 0.881 ***<br>(0.0309)   |
| Number of offices                                       | 0.124<br>(0.0768)                      | 0.124<br>(0.0770)                      | 0.00760<br>(0.0371)      | 0.00753<br>(0.0372)      | −0.154 **<br>(0.0613)                  | −0.154 **<br>(0.0613)   |
| Number of employees                                     | 0.00321 *<br>(0.00188)                 | 0.00322 *<br>(0.00188)                 | −0.00231<br>(0.00361)    | −0.00230<br>(0.00362)    | 0.00432 **<br>(0.00173)                | 0.00434 **<br>(0.00173) |
| Per capita income in<br>logs                            | −0.201 **<br>(0.0784)                  | −0.200 **<br>(0.0785)                  | −0.210 ***<br>(0.0758)   | −0.208 ***<br>(0.0759)   | −0.0666<br>(0.0490)                    | −0.0669<br>(0.0491)     |
| SPEI Drought                                            | 0.00737<br>(0.0325)                    | −0.0485<br>(0.0566)                    | 0.0177<br>(0.0255)       | −0.0626<br>(0.0432)      | 0.0187<br>(0.0176)                     | 0.0433<br>(0.0303)      |
| SPEI Drought ×<br>Distance to nearest<br>market         | −0.0505<br>(0.0500)                    | 0.155 *<br>(0.0903)                    | −0.0587<br>(0.0435)      | −0.113<br>(0.0934)       | 0.0405<br>(0.0348)                     | 0.0344<br>(0.0711)      |
| SPEI Rainy                                              | −0.0246<br>(0.0316)                    | −0.0949 *<br>(0.0563)                  | −0.0239<br>(0.0274)      | −0.0146<br>(0.0435)      | 0.0156<br>(0.0192)                     | 0.0153<br>(0.0308)      |
| SPEI Rainy × Distance<br>to nearest market              | −0.0495<br>(0.0504)                    | −0.00938<br>(0.101)                    | −0.0452<br>(0.0402)      | −0.0650<br>(0.0846)      | 0.0617 *<br>(0.0365)                   | 0.138 **<br>(0.0679)    |
| SPEI Drought (t − 1)                                    | −1.12 × 10 <sup>−5</sup><br>(0.000207) | 0.000223<br>(0.000351)                 | −0.000224<br>(0.000167)  | 0.000180<br>(0.000272)   | −2.18 × 10 <sup>−5</sup><br>(0.000116) | −0.000148<br>(0.000208) |
| SPEI Drought (t − 1) ×<br>Distance to nearest<br>market | 0.000603 *<br>(0.000316)               | −0.000544<br>(0.000540)                | 0.000496 *<br>(0.000277) | 0.000983 *<br>(0.000595) | −0.000123<br>(0.000214)                | −0.000165<br>(0.000402) |
| SPEI Rainy (t − 1)                                      | 8.56 × 10 <sup>−6</sup><br>(0.000209)  | 0.000647 *<br>(0.000376)               | 0.000148<br>(0.000171)   | 0.000118<br>(0.000276)   | 7.57 × 10 <sup>−5</sup><br>(0.000138)  | 0.000172<br>(0.000218)  |
| SPEI Rainy (t − 1) ×<br>Distance to nearest<br>market   | 0.000609 *<br>(0.000319)               | −3.19 × 10 <sup>−5</sup><br>(0.000588) | 0.000363<br>(0.000267)   | 0.000603<br>(0.000597)   | −0.000251<br>(0.000226)                | −0.000663<br>(0.000405) |
| Observations                                            | 42,117                                 | 42,117                                 | 40,492                   | 40,492                   | 39,161                                 | 39,161                  |
| R-squared                                               | 0.778                                  | 0.778                                  | 0.890                    | 0.890                    | 0.877                                  | 0.877                   |

Note: Standard errors with cluster at the municipality-entity level are in parentheses. All regressions include time and municipality-entity fixed effects. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

### 5.4. Hypotheses Validation

In this section, we review and validate our working hypotheses. Table 6 shows how each fares across the different specifications. Each complete validation (sign, significance and size) is considered a success (✓); anything less than that is a partial validation. There is no validation at all for hypotheses H1b, H3b, and H4b. There is no evidence that high-precipitation shocks, contemporaneous and lagged, and high-temperature shocks affect credit risk in any segment. For the remaining hypotheses, we find at least partial evidence of an association between segments' credit risk and the different shocks we consider. Low-temperature shocks, contemporaneous and lagged, have a widespread impact. For the

drought and rainy shocks, we also find partial evidence of impact on credit risk, especially for the microcredit segment.

**Table 6.** Hypotheses validation.

| Hypotheses | Identifier                     | Impact on CRI | Table    | Commercial | Segment<br>Consumer | Microcredit |
|------------|--------------------------------|---------------|----------|------------|---------------------|-------------|
| H1a        | Low-Precipitation Shock (LPS)  | + (Positive)  | Table 1  |            |                     | ✓           |
|            |                                |               | Table A1 |            |                     | ✓           |
|            |                                |               | Table 2  |            | ✓-Partial           |             |
| H1b        | High-Precipitation Shock (HPS) | +             | Table 1  |            |                     |             |
|            |                                |               | Table A1 |            |                     |             |
|            |                                |               | Table 2  |            |                     |             |
| H2a        | Low-Temperature Shock (LTS)    | +             | Table 1  |            | ✓                   |             |
|            |                                |               | Table A1 |            | ✓                   |             |
|            |                                |               | Table 2  | ✓          | ✓                   | ✓           |
| H2b        | High-Temperature Shock (HTS)   | +             | Table 1  |            |                     |             |
|            |                                |               | Table A1 |            |                     |             |
|            |                                |               | Table 2  |            |                     |             |
| H3a        | Lagged—LPS                     | + & Lg > Cont | Table 1  |            |                     | ✓-Partial   |
|            |                                |               | Table A1 |            |                     | ✓           |
|            |                                |               | Table 2  |            |                     |             |
| H3b        | Lagged—HPS                     | + & Lg > Cont | Table 1  |            |                     |             |
|            |                                |               | Table A1 |            |                     |             |
|            |                                |               | Table 2  |            |                     |             |
| H4a        | Lagged—LTS                     | + & Lg > Cont | Table 1  |            | ✓                   |             |
|            |                                |               | Table A1 | ✓          | ✓                   |             |
|            |                                |               | Table 2  | ✓-Partial  | ✓                   | ✓-Partial   |
| H4b        | Lagged—HTS                     | + & Lg > Cont | Table 1  |            |                     |             |
|            |                                |               | Table A1 |            |                     |             |
|            |                                |               | Table 2  |            |                     | ×-Opposite  |
| H5a        | Drought                        | +             | Table 3  |            |                     | ✓-Partial   |
| H5b        | Rainy                          | +             | Table 3  | ✓-Partial  |                     |             |
| H6a        | Lagged—Drought                 | + & >Cont     | Table 3  |            |                     | ✓-Partial   |
| H6b        | Lagged—Rainy                   | + & >Cont     | Table 3  |            |                     | ✓           |
| H7         | Per Capita Income              | − (Negative)  | Table 1  | ✓          | ✓                   |             |
|            |                                |               | Table A1 | ✓          | ✓                   | ✓           |
|            |                                |               | Table 2  |            |                     |             |
|            |                                |               | Table 3  | ✓          | ✓                   |             |
|            |                                |               | Table 4  | ✓          | ✓                   |             |
|            |                                |               | Table 5  | ✓          | ✓                   |             |
| H8         | Distance to Market             | +             | Table 5  | ✓-Partial  | ✓-Partial           | ✓-Partial   |

Finally, complementary hypotheses are also validated. Per capita income and distance to market affect credit risk in the hypothesized sense, highlighting the importance of identifying market and customer characteristics that can mitigate or exacerbate credit risk and the impact of weather shocks.

### 5.5. Discussion

Climate change is affecting all human activities (Meneses Cerón et al., 2024). But some individuals and entities are particularly sensitive to climate and could provide valuable information to financial intermediaries and authorities looking to improve climate risk management techniques (Zhang et al., 2023). Individuals and firms in small municipalities whose primary activity is agriculture should be particularly affected by weather shocks. Thus, we aimed to study the credit behavior of loans granted by financial institutions in this universe. This market is served by a few Colombian banks, particularly Banco Agrario, a state bank, whose explicit purpose is to serve this sector. Firstly, we structured two databases, a credit database organized by municipality and bank and a climate database measuring temperature and rain levels. Our sources are CFS for the credit data and CHIRPS (precipitation levels), Copernicus (temperature levels) and SPEI (rainy and drought periods) for the weather data. Understandably CRI lowers with income levels. A two-dimensional analysis of the relationship between precipitation levels shows heterogeneous results depending on the credit type. Consumer credit risk index increases with low temperature shocks and exhibit dependence from the nearest market. Commercial credit, on the other hand, is the least affected, with CRI effects by low-temperature shocks restricted to the Banco Agrario sample. Microcredit CRI, understandably, is the most affected. Low-precipitation and low-temperature shocks affect its CRI, as well as SPEI drought and rainy shocks. Microcredit CRI also exhibits some resilience by lowering its CRI when affected from prior shocks, although most of our results are susceptible to the potential bias of being previously exposed to shocks. Finally, all segments suffer to some degree when the loans come from municipalities far from the nearest and natural market. Interestingly, in municipalities where Banco Agrario is the sole credit provider, low-temperature shocks have a widespread impact, in both current and lagged shocks. For the SPEI, current rainy shocks affect commercial CRI. In general, there is evidence of climate shocks influencing credit behavior, which requires further analysis. Banks should develop their own models to learn how to reduce their exposure to climate shocks. Analysis incorporating debtors' specific information and bank policies could uncover useful patterns to shield banks and debtors from some of the harmful impacts of the current climate conundrum. Customers can also gain from banks learning about the development of products with some natural or purchased hedge.

## 6. Conclusions

Developing countries like Colombia critically need to ensure the viability of small farmers' way of life. High violence levels and low access to health and education hinder their welfare. Increased climate risks add an additional burden to their difficulties. High levels of delinquency can reduce banks' incentives to offer loans to rural areas. This trend worsens access to funds.

Our models allowed us to test the relationship between weather shocks and credit risk. By concentrating our efforts in small rural municipalities, we focus on the most vulnerable sectors of the population. The main contribution of this study lies in providing robust microeconomic evidence that climate shocks are transmitted differentially to credit risk in rural contexts, depending on both the type of credit and the structure of the financial market. In particular, the research demonstrates that microcredit loans are especially vulnerable

to droughts and high temperatures, reflecting their close relationship with agricultural activities; whereas consumer loans respond more sensitively to temperature shocks, and commercial loans exhibit relatively lower exposure. Likewise, the study evidences that institutional structure matters: in municipalities where a monopoly provider exists, the effects of climate shocks on risk are more intense and widespread, suggesting that a lack of competition amplifies financial vulnerability. In a novel manner, it also finds that historical exposure to extreme events does not necessarily generate resilience in terms of credit risk, challenging the hypothesis of automatic adaptation in rural populations.

While the methodological approach employed provides relevant evidence, it can and should be further refined in future research. Understanding and managing the effects of climate shocks constitutes a social and economic imperative, particularly in vulnerable rural contexts. In this regard, a research agenda emerges that is critical for advancing the understanding of the nexus between climate risk and financial risk. First, it is necessary to assess whether credit schemes oriented toward sustainable practices can contribute to reducing the credit risk index (CRI). Second, the role of financial institutions in developing financial and climate literacy strategies should be examined, particularly in terms of strengthening borrowers' capacity to manage their exposure to environmental risks. Third, it is essential to explore the interaction between credit risk and structural territorial factors, such as municipal-level violence. Furthermore, future research should delve into the potential of innovative instruments, such as parametric or index-based insurance, to mitigate the effects of climate shocks on loan portfolios. It is also important to analyze whether prior exposure to extreme weather events fosters adaptation and resilience processes that translate into lower delinquency rates, acknowledging that this potential effect may coexist with adverse dynamics, such as increases in interest rates and slower post-event economic recovery. Overall, the management and assessment of rural credit risk emerges as a complex challenge that requires the development of comprehensive approaches, the use of more granular data, and the incorporation of novel analytical methodologies, with the aim of strengthening the resilience of both the financial system and households in the face of increasing climate-related risks.

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## Appendix A

Tests with other definitions of CRI.

**Table A1.** Risky loans and weather shocks—alternative definition of CRI.

|                                         | (1)                      | (2)                      | (3)                                | (4)                                | (5)                      | (6)                      |
|-----------------------------------------|--------------------------|--------------------------|------------------------------------|------------------------------------|--------------------------|--------------------------|
|                                         | Shocks at<br>90% and 10% | Shocks at<br>80% and 20% | Shocks at<br>90% and 10%           | Shocks at<br>80% and 20%           | Shocks at<br>90% and 10% | Shocks at<br>80% and 20% |
| Dep. Var.: Portfolio<br>at Risk in Logs | Commercial               |                          | Consumer                           |                                    | Microcredits             |                          |
| Portfolio balance in<br>logs            | 0.527 ***<br>(0.0269)    | 0.527 ***<br>(0.0268)    | 0.761 ***<br>(0.0266)              | 0.761 ***<br>(0.0266)              | 0.833 ***<br>(0.0260)    | 0.833 ***<br>(0.0260)    |
| Number of offices                       | 0.222 ***<br>(0.0791)    | 0.222 ***<br>(0.0790)    | −0.00161<br>(0.0327)               | −0.00175<br>(0.0326)               | −0.145 ***<br>(0.0553)   | −0.145 ***<br>(0.0553)   |
| Number of<br>employees                  | 0.00205<br>(0.00132)     | 0.00205<br>(0.00132)     | $2.69 \times 10^{-5}$<br>(0.00233) | $2.11 \times 10^{-5}$<br>(0.00233) | 0.00208<br>(0.00207)     | 0.00208<br>(0.00207)     |
| Per capita income in<br>logs            | −0.293 ***<br>(0.0825)   | −0.293 ***<br>(0.0825)   | −0.229 ***<br>(0.0745)             | −0.227 ***<br>(0.0745)             | −0.0875 *<br>(0.0522)    | −0.0878 *<br>(0.0521)    |
| Low-precipitation<br>shock              | 0.00416<br>(0.0177)      | 0.0104<br>(0.0147)       | −0.000276<br>(0.0142)              | 0.00262<br>(0.0116)                | 0.0222 **<br>(0.00975)   | 0.0152 *<br>(0.00822)    |
| High-precipitation<br>shock             | −0.00206<br>(0.0176)     | 0.00918<br>(0.0156)      | −0.00241<br>(0.0135)               | −0.00130<br>(0.0116)               | −0.000966<br>(0.0104)    | 0.00228<br>(0.00915)     |
| Low-temperature<br>shock                | 0.0464<br>(0.194)        | 0.0250<br>(0.135)        | 0.648 ***<br>(0.154)               | 0.494 ***<br>(0.114)               | 0.0917<br>(0.121)        | 0.0345<br>(0.0867)       |
| High-temperature<br>shock               | 0.000904<br>(0.0561)     | −0.0405<br>(0.0528)      | −0.0174<br>(0.0456)                | −0.0372<br>(0.0419)                | 0.0555<br>(0.0359)       | 0.0314<br>(0.0328)       |
| Low-precipitation<br>shock (t − 1)      | 0.0193<br>(0.0170)       | 0.0174<br>(0.0145)       | −0.0171<br>(0.0139)                | −0.00165<br>(0.0110)               | 0.0181 *<br>(0.0107)     | 0.0154 *<br>(0.00897)    |
| High-precipitation<br>shock (t − 1)     | 0.0168<br>(0.0182)       | 0.0210<br>(0.0157)       | −0.000192<br>(0.0135)              | −0.00147<br>(0.0118)               | −0.00234<br>(0.0108)     | 0.00156<br>(0.0100)      |
| Low-temperature<br>shock (t − 1)        | 0.199<br>(0.195)         | 0.166<br>(0.137)         | 0.636 ***<br>(0.159)               | 0.478 ***<br>(0.113)               | 0.0508<br>(0.116)        | 0.000379<br>(0.0805)     |
| High-temperature<br>shock (t − 1)       | 0.0394<br>(0.0633)       | 0.00241<br>(0.0569)      | −0.00919<br>(0.0480)               | −0.0127<br>(0.0445)                | 0.0281<br>(0.0386)       | 0.0109<br>(0.0360)       |
| Observations                            | 48,324                   | 48,324                   | 47,523                             | 47,523                             | 47,755                   | 47,755                   |
| R-squared                               | 0.719                    | 0.719                    | 0.878                              | 0.878                              | 0.856                    | 0.856                    |

Note: Standard errors with cluster at the municipality-entity level are in parentheses. All regressions include time and municipality-entity fixed effects. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## References

- Adjognon, G. S., Liverpool-Tasie, L. S., & Shupp, R. (2020). Productivity shocks and repayment behavior in rural credit markets: A framed field experiment. *The Journal of Development Studies*, 56(10), 1909–1926. [CrossRef]
- Aguilar-Gomez, S., Gutierrez, E., Heres, D., Jaume, D., & Tobal, M. (2024). Thermal stress and financial distress: Extreme temperatures and firms' loan defaults in Mexico. *Journal of Development Economics*, 168(103246), 1–19. [CrossRef]
- Anderson, E., Khaykin, I., Pyanet, A., & Schuermann, T. (2021). *Banks and climate change risk*. Available online: <https://ssrn.com/abstract=3964224> (accessed on 30 November 2025). [CrossRef]
- Brik, H. (2024). Climate risk and financial stability: Assessing non-performing loans in Chinese banks. *Journal of Risk Management in Financial Institutions*, 17(3), 303–315. [CrossRef]
- Bunn, P., Le Roux, J., Reinold, K., & Surico, P. (2018). The consumption response to positive and negative income shocks. *Journal of Monetary Economics*, 96, 1–15. [CrossRef]

- Calabrese, R., Dombrowski, T., Mandel, A., Pace, R., & Zanin, L. (2024). Impacts of extreme weather events on mortgage risks and their evolution under climate change: A case study on Florida. *European Journal of Operational Research*, 34(1), 377–392. [CrossRef]
- Castro, C., & Garcia, K. (2014). Default risk in agricultural lending, the effects of commodity price volatility and climate. *Agricultural Finance Review*, 74(4), 501–521. [CrossRef]
- Chen, S., Xu, Q., Zeng, J., & Zhao, Y. (2024). *Ark amidst extreme weather: Evidence from personal credit at a chinese bank*. Available online: <https://ssrn.com/abstract=4848473> (accessed on 30 November 2025). [CrossRef]
- Cohen, I., Zandalinas, S. I., Huck, C., Fritschi, F. B., & Mittler, R. (2021). Meta-analysis of drought and heat stress combination impact on crop yield and yield components. *Physiologia Plantarum*, 171(1), 66–76. [CrossRef] [PubMed]
- Colarieti, R., Mei, P., & Stantcheva, S. (2024). *The how and why of household reactions to income shocks*. No. w32191. National Bureau of Economic Research.
- Cole, S. A., & Xiong, W. (2017). Agricultural insurance and economic development. *Annual Review of Economics*, 9, 235–262. [CrossRef]
- Conning, J., & Udry, C. (2007). Rural financial markets in developing countries. In *Handbook of agricultural economics* (vol. 3, pp. 2857–2908). Elsevier. [CrossRef]
- Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate–economy literature. *Journal of Economic Literature*, 52(3), 740–798. [CrossRef]
- Greig, B., Nuthall, P., & Old, K. (2019). Resilience and finances on Aotearoa New Zealand farms: Evidence from a random survey on the sources and uses of debt. *New Zealand Geographer*, 75(1), 21–33. [CrossRef]
- Liliane, T. N., & Charles, M. S. (2020). Factors affecting yield of crops. In *Agronomy-climate change and food security* (pp. 1–16). IntechOpen. [CrossRef]
- Meierrieks, D. (2021). Weather shocks, climate change and human health. *World Development*, 138, 105228. [CrossRef]
- Meneses Cerón, L. Á., van Klyton, A., Rojas, A., & Muñoz, J. (2024). Climate risk and its impact on the cost of capital—A systematic literature review. *Sustainability*, 16(23), 10727. [CrossRef]
- Moahid, M., Khan, G. D., Bari, M. A., & Yoshida, Y. (2023). Does access to agricultural credit help disasteraffected farming households to invest more on agricultural input? *Agricultural Finance Review*, 83(1), 96–106. [CrossRef]
- Nguyen, T. T., Nguyen, T. T., & Grote, U. (2023). Credit, shocks and production efficiency of rice farmers in Vietnam. *Economic Analysis and Policy*, 77, 780–791. [CrossRef]
- Nie, O., Regelink, M., & Wang, D. (2023). *Banking sector risk in the aftermath of climate change and environmental-related natural disasters*. Policy Research Working Paper Series 10326. The World Bank.
- Oliveira, G. R. (2022). Effects of climate on bank default. *Revista Brasileira De Climatologia*, 30(18), 402–423. [CrossRef]
- Phan, T., & Schwartzman, F. (2023). *Climate defaults and financial adaptation* (pp. 1–39). Federal Reserve Bank of Richmond Working Papers 23-06. Federal Reserve Bank of Richmond. [CrossRef]
- Thakur, P., Kumar, S., Malik, J. A., Berger, J. D., & Nayyar, H. (2010). Cold stress effects on reproductive development in grain crops: An overview. *Environmental and Experimental Botany*, 67(3), 429–443. [CrossRef]
- Thorntwaite, C. W. (1948). An approach toward a rational classification of climate. *Geographical Review*, 38(1), 55–94. [CrossRef] [PubMed]
- UN Environment Programme. (2022). *Emissions gap report 2022*. Available online: <https://www.unep.org/resources/emissions-gap-report-2022> (accessed on 30 November 2025).
- Vicente-Serrano, S. M., Beguería, S., & Lopez-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *Journal of Climate*, 23(7), 1696–1718. [CrossRef]
- Wong, M. C. S., & Ho, H. M. (2023). A framework for integrating extreme weather risk, probability of default, and loss given default for residential mortgage loans. *Sustainability*, 15(15), 11808. [CrossRef]
- Wu, X., Bai, X., Qi, H., Lu, L., Yang, M., & Taghizadeh-Hesary, F. (2023). The impact of climate change on banking systemic risk. *Economic Analysis and Policy*, 78, 419–437. [CrossRef]
- Zhang, X., Zhang, M., & Fang, Z. (2023). Impact of climate risk on the financial performance and financial policies of enterprises. *Sustainability*, 15(20), 14833. [CrossRef]

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