Dry Weather, Dry Wallet? Heterogeneous Uses of Financial Tools during Dryness in a Middle-Income Economy

BY

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Abstract

This paper examines how populations with different sociodemographic characteristics use distinct financial tools to cope with drought-related distress, and the implications for future access to credit. We use various datasets, including a proprietary database on credit card loans and non-revolving consumer credit in Mexico—a middle-income economy with shallow credit markets and limited access to formal credit. Our findings show that droughts reduce agricultural output and employment in affected regions, leading to increased credit card loans' delinquency driven by a rise in non-performing loans— suggesting that droughts generate financial distress and impair repayment capacity in Mexico. The effects are heterogeneous: those living in less vulnerable regions, with higher education and formal employment, access a broader range of financial tools under favorable terms and draw on savings or remittances to avoid falling into credit delinquency. In contrast, those in more vulnerable areas with high labor informality levels rely mainly on costly credit card loans, increasing their risk of default. These findings suggest that droughts can function as poverty traps, with rising delinquency further restricting access to future credit by vulnerable individuals under favorable terms.

JEL Codes: G51, I30, Q54

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Introduction

Droughts are prolonged periods of dryness that reduce both the quantity and quality of water, disrupting economic activity in affected regions. This is particularly true for water-dependent sectors, such as agriculture, where reduced output can lead to lower firm revenues, job losses, and harm to households' incomes. Some affected people may rely on credit or other financial tools to smooth consumption and cope with the income shock. Others, however, lack access to credit or refinancing options and may ultimately have to default on existing credit obligations. Understanding how people with different characteristics respond to drought-related financial distress is becoming increasingly important, especially as droughts can increase in frequency and intensity going forward due to higher global temperatures and climate change (IPCC, 2021; Williams et al., 2020). However, our understanding of financial responses to droughts and the ensuing implications for future access to credit remains limited, hindering the development of effective policy responses.

This is the first paper to study the use of different financing tools by affected people with different characteristics in coping with drought-induced financial stress. We exploit exogenous variation from unusually extreme droughts to analyze the use of a range of financial tools, namely, credit card loans, non-revolving consumer loans, savings, and remittances in a middle-income country with a credit market that is not profound—Mexico. Our findings clearly show marked heterogeneous responses that can be summarized in two groups. The first group of responses corresponds to people living in less vulnerable regions with better education and higher levels of formal jobs, with access to credit card loans and non-revolving credit under favorable terms, and using their savings and remittances to avoid falling into credit delinquency.

In contrast, the second group comprises individuals from more vulnerable regions and higher levels of labor informality, making it hard to access high-quality non-revolving credit or savings in periods of financial distress. They mostly have access to credit card loans—the most widespread form of consumer credit—which offer pre-approved revolving lines but under worse terms than those available to resilient individuals. We find evidence that individuals in this second group tend to rely on these costly credit lines, which increases their likelihood of default later on. These findings imply that more vulnerable individual lack the financial tools to smooth consumption during droughts and their temporary economic

hardship can become poverty traps and have longer-term economic consequences than initially expected, as credit defaults are part of the individual's credit history and their record is kept in the credit bureau for up to six years, affecting future access to credit.

Throughout the analysis, we identify droughts using data from the Drought Monitor of the Mexican National Commission of Water (CONAGUA).[1] This Monitor identifies municipalities experiencing droughts and classifies them by severity every two weeks, using five categories ranging from D0 to D4 (abnormal, moderate, severe, extreme, and exceptional droughts).[2] Our data covers a nine-year period, from 2016 to 2024, for which we have data on revolving credit. We use D3 and D4 categories to focus only on the most harmful droughts to compare changes in the use of financial tools in regions that are exposed to unusual dryness to the same changes in municipalities that are not exposed to unusual dryness. The identification strategy relies on the assumption that these droughts are exogenous after controlling for seasonality and time trends specific to each municipality, as well as for national-level changes in credit delinquency rates over time.

Our analysis begins by verifying that extreme drought disrupts economic activity by impacting production. Using data at the municipal level from the Agroalimentary and Fisheries Information Service (SIAP), we estimate the effects of droughts on agricultural production, which may be disrupted the most due to dryness and decreased access to water.[3] Our findings show that, indeed, regions subject to extreme drought experience a significant reduction in agricultural production. Lower levels of agricultural production can disrupt the economy of exposed regions through at least two channels. First, lower levels of production can lead to lower revenues for firms, which may, in turn, translate into lower employment levels (Afridi et al., 2022; Mueller & Osgood, 2009). Second, municipalities with a greater concentration of agricultural labor can also be more vulnerable through general equilibrium effects from a reduction in local aggregate demand, as these regions often have lower income levels and are less developed (Aguilar-Gomez et al., 2024).

[11] Previous research has used drought monitor data to characterized droughts and to estimate their effects on economic outcomes, such as agricultural production in the United States (Kuwayama et al., 2019; Leeper et al., 2022).
[2] The categorization follows the methodology of the United States Drought Monitor.
[3] As further explain in Section II, in Mexico, the agricultural sector uses 67% of water, significantly more than any other economic sector or the urban use of the population.

We test the effects on employment using publicly available data at the municipal level on the total number of employees reporting formal wages to the Mexican Social Security Institute (IMSS). We estimate the effects on employment for the average municipality as well as the employment in agricultural and non-agricultural intensive regions to verify that the effects are more pronounced in agricultural municipalities. Our findings reveal that regions hit by extreme droughts experience a significant decline in employment levels and, consistent with our hypothesis, this decline is driven by an employment reduction in agricultural municipalities.

To cope with the drought-related income shock, individuals may use their available financial tools. Most individuals in Mexico declare to use credit cards, other types of credit, their own savings, or transfers from relatives when their monthly earnings are not enough to cover their monthly expenses. We analyze all of these financial tools one at a time. We start by looking at their use of credit cards, as this tool has two important characteristics for our analysis. First, credit card loans are the most available consumer credit in terms of number, outstanding credit amount, and presence across municipalities in Mexico. Second, credit cards have pre-approved revolving credit lines that can be used by individuals as needed, unlike non-revolving credit that requires a special creditworthiness assessment every time it is granted. Having a pre-approved credit line is important in overcoming access barriers of economies with shallow credit markets, such as Mexico. In this type of markets, financial intermediaries often do not meet the liquidity demands of economic agents with limited credit histories and fewer assets to pledge as collateral, such as small- and medium-enterprises (SMEs) in the case of firms, or first-time borrowers in the case of individuals (Aguilar-Gomez et al., 2024; Berg & Schrader, 2012).

In our credit card analysis, we exploit a detailed proprietary dataset containing information on the universe of credit card loans extended by commercial banks. First, we use bi-monthly data to investigate if an increase in the number of weeks of extreme droughts in a municipality in the last year leads to increases in credit delinquency in that region. We present five specifications that test the robustness of the results using an increasing set of fixed-effects that capture within-bank, within-municipality, borrower-specific, and seasonal variation. Regardless of the specification, our findings show that, for every ten weeks of exposure to extreme droughts over a one-year window, the credit card loans' delinquency

rate rises by around 0.10 percentage points, which represents 1.6 percent of the mean delinquency rate in the sample.

As the delinquency rate is built as the ratio of non-performing loans to total outstanding credit, we break down the delinquency rate to assess whether this increase is driven by changes in performing or non-performing credit. We estimate these effects for the entire sample, as well as for agricultural and non-agricultural intensive regions, to test whether credit delinquency increases precisely in the municipalities that suffer more from the shock. Our findings reveal that the increase in credit delinquency is only explained by an increase in non-performing loans concentrated in agricultural-intensive municipalities. For these regions, we find that non-performing loans increase by 4.1% for every 10 weeks of unusual droughts, which translates into delinquency rates rising by 0.128 percentage points (2% of the sample mean). In contrast, regardless of the sample, we find no statistically significant changes in the extensive margin measured by the number of credit card loans. Taken together, these findings suggest that the exposure to droughts harmed the ability of individuals to repay their loans, increasing credit default, while the lack of changes in the number of new credit card loans is in line with the lack of response of financial intermediaries to liquidity demands that require a special granting assessment after a shock.

Drought-related liquidity problems could vary based on sociodemographic characteristics. For instance, individuals living in regions with higher levels of labor informality or lower education levels could be more vulnerable to financial shocks, consistent with the idea that lower-skilled individuals lose their jobs first in times of economic downturns (Kugler et al., 2023). We explore these dimensions by dividing the sample of agricultural-intensive municipalities based on socioeconomic characteristics. Specifically, we divide the sample based on labor informality, education, and poverty levels. Our findings confirm that the negative effects of droughts are more pronounced for individuals living in regions with lower education levels, more poverty, and higher levels of labor informality.

These worse socioeconomic characteristics may also translate to more binding borrowing conditions, as individuals in these regions often face higher information asymmetries and have fewer assets to pledge as collateral, further constraining their financing options. We explore this hypothesis by dividing the sample based on credit conditions: interest rate, credit line size, and absolute distance to the credit card limit. Consistent with our hypothesis, the

findings reveal that the negative effects of droughts are concentrated on individuals with the worst credit conditions, meaning higher interest rates, lower credit card lines, and less distance to the credit card limit. So, when using credit card loans, the borrowing conditions make it harder for these individuals to repay their credit obligations.

Individuals in exposed regions can also use other financing tools instead. One alternative is other credit tools, such as non-revolving consumer credit, which, contrary to the pre-approved revolving lines of credit card loans, requires a special creditworthiness assessment each time it is granted. Using a detailed proprietary dataset with loan and individual characteristics, we explore the use of non-revolving credit after a drought. We categorize non-revolving credit segments by loan conditions and examine their differential responses. For simplicity, we term "low-quality loans" those with the highest interest rates, smallest amounts, highest default probabilities, and shortest maturities; in our sample, this includes the credit segments comprising personal loans and durable-goods loans. In contrast, "high-quality loans" are those with the lowest interest rates, largest amounts, lowest default probabilities, and longest maturities, including automotive and salary-based loans—where payments are directly debited from the borrower's account—typically associated with the formal economy.

For the total sample of non-revolving credit and for the sample of low-quality loans, we find no statistically significant changes in either the intensive margin (delinquency rate, performing or non-performing loans) or in the extensive margin (number of loans). In contrast, our findings show an increase in both the intensive and extensive margins for high-quality loans. In the intensive margin, we find a statistically significant uptake of 1.6 percent in performing credit, which drives up the total outstanding credit by 1.3 percent. Lined up with these results, in the extensive margin, we find a statistically significant increase of 0.4 percent in the number of loans. These findings imply that there is a group of individuals who can access non-revolving credit with the best borrowing conditions after a drought without negative effects on credit delinquency, and there is another group of individuals in exposed regions that do not (or cannot) access these loans to cope with financial distress.

In this context, individuals in agricultural-intensive regions may also turn to non-credit financial tools to cope with the shock. Using data at the municipal level from the National Banking and Stock Commission (CNBV), we study the use of deposits, which we use as a

proxy of liquid savings, after a drought. Our findings show a statistically significant decline of 3.8 percent in deposits at agricultural-intensive regions for every one more week of drought, suggesting that individuals make use of savings to cope with the financial shock. Moreover, we find evidence that, in doing so, individuals in exposed regions use savings to avoid credit default. Our findings reveal that credit card loans' delinquency increases only 0.09 percentage points in agricultural-intensive municipalities with a greater savings per capita, much less than the 0.22 percentage points increase in exposed municipalities with a lower per capita availability of deposits to cope with the shock.

We also explore whether individuals in exposed regions use remittances. Remittances are an important source of income in Mexico, reaching almost all municipalities and representing 3.5 percent of the country's GDP (CONAPO & Fundación BBVA, 2024). Using quarterly data from the Mexican Central Bank (Banxico), we estimate the use of remittances after a drought. Our findings show a statistically significant increase in remittances both in agricultural and non-agricultural intensive regions, with the increase in exposed regions almost 3 times greater. Also, lined up with the use of savings, we find evidence that individuals in exposed regions use remittances to avoid credit default[4]. Our findings reveal that exposed municipalities with greater remittance levels do not experience a statistically significant increase in credit card delinquency after a drought. In contrast, individuals in agricultural intensive municipalities with lower remittance levels show a statistically significant rise of 0.22 percentage points in their delinquency rate. This finding is consistent with these households lacking other financial tools to cope with the fall of their repayment capacity caused by droughts.

Finally, we explore whether the lack of effect on performing credit in our analysis for the average bimester could be hindering different individual responses based on seasonal spending obligations. For instance, our data shows that performing credit card transactions in December is 9.9% above the annual mean, probably explained by the end-of-year financial commitments, such as the holidays and family gatherings. In doing so, we break down the analysis by bimester (the maximum granularity allowed by the credit data) to explore seasonal variations in the intensive and extensive margins of credit card loans. In line with

[4] This is consistent with Heres et al. (2022), who find that a positive remittance shock declines credit default due to some households using this extra income to repay their existing loans that otherwise would default.

the rise in liquidity needs during the holiday season, we find that an increase on performing credit card loans, peaking at the end of the year. This surge in credit use is followed by a rise in the delinquency rate two bimesters later, reflecting the 90-day threshold for a loan to be classified as delinquent. This pattern suggests that increased credit card use due to dryness at the end of the year ultimately leads to credit default.[5]

We further explore the credit conditions of the individuals who are driving this increase in performing credit that eventually leads to default. Our findings show that individuals in exposed regions with the worst credit conditions are the ones driving this uptake in performing loans. Moreover, we divide the samples of savings and remittances based on credit conditions to estimate the use of these tools as substitutes for credit delinquency. Our findings reveal that individuals with the best borrowing conditions are the ones with the largest use of remittances and deposits after a drought.

Taken together, these findings reinforce the story of one group composed of more resilient individuals who can access credit under better borrowing conditions and use other financing tools to avoid default in periods of financial distress. In contrast, there is a group of more vulnerable individuals with worse socioeconomic characteristics that constrain their access to credit. They only have access to credit card loans, which are the most widespread type of consumer credit, and have pre-approved revolving lines, but under worse credit conditions than resilient individuals and with fewer alternative tools to substitute for credit delinquency, further excluding them from the credit market in the future.

This paper makes three main contributions. First, by leveraging data of credit card loans, non-revolving consumer credit, deposits, and remittances, we are able to have a more complete understanding of how individuals use different financing tools when coping with a weather shock in an middle-income economy, where there is a greater vulnerability to weather shocks and less available financing tools (Mertz et al., 2009).[6] Previous research on this strand has studied the effects on individuals living in high-income economies,

[5] When running the same seasonality analysis for the case of non-revolving loans, we also find an increase in performing loans, but it is two months later than December and of smaller magnitude than revolving credit, consistent with a lagged response and lower loan amounts due to the need for credit approval. As in revolving loans, this increase in credit leads to default two bimesters later.

[6] The unequal exposure and adaptability to climate change between middle- and high income economies has also been documented in policy reports of international organizations such as the IMF. For instance, please see: Poor and Vulnerable Countries Need Support to Adapt to Climate Change (imf.org)

particularly in the United States (Deryugina, 2017; Dobridge, 2018; Gallagher, 2014; Gallagher & Hartley, 2017). For instance, Gallagher (2014) shows that individuals increase their insurance take-up the year after a flood, suggesting that the occurrence of a flood updates their expectations of experiencing extreme weather events. Our findings on the use and combination of financing tools, complement these previous results from the literature, and are particularly relevant for settings with lower insurance penetration and weaker government support.

Second, the present paper contributes to the emerging literature on the effects of weather shocks on financial outcomes by showing that results are heterogeneous by group of individuals and type of credit. Specifically, our findings show that revolving credit may be a more available credit tool after a weather shock due to their pre-approved credit lines. This finding is particularly important for countries with shallow credit markets, where banks reduce credit supply after a shock, especially for first-time clients and SMEs (Aguilar-Gomez et al., 2024; Berg & Schrader, 2012), which face similar credit constraints as our groups of individuals from more vulnerable regions. This literature has mostly focused on the effects on firms' credit (Aguilar-Gomez et al., 2024; Brown et al., 2021; Collier et al., 2020), with only a small set of studies analyzing the effects of weather shocks on consumer credit in the United States (Dobridge, 2018; Gallagher & Hartley, 2017).

Third, we provide a more complete picture of the effects of droughts on economic outcomes by linking their effects on production and employment to the individuals' use of financing tools after the drought, their heterogenous responses, and longer-term consequences. For instance, by showing that the coping strategy of individuals from more vulnerable regions leads to credit default, we are providing evidence suggesting that droughts can become poverty traps, as credit default adversely affects future access to credit. This relates to the literature studying the impact of weather shocks on economic outcomes, which has documented the effects of weather shocks on different outcomes including economic output (Burke et al., 2015; Dell et al., 2012; Strobl, 2011, 2012), income (Deryugina et al., 2018), employment, and migration (Baez et al., 2017; Jessoe et al., 2018; Liu et al., 2023).

In the remainder of the paper, Section II introduces the institutional framework of our analysis. Section III describes our data sources, and Section IV outlines the empirical strategy. Section V presents the results. Finally, Section VI concludes.

II. Institutional Framework

Dryness in Mexico

Mexico's geographical and climatological characteristics make it suitable for the analysis of droughts. Its territorial extension (top 15th worldwide) allows the existence of different temperatures and ecosystems, but the presence of a high-pressure belt that constrains the formation of clouds—and rain—makes it particularly susceptible to experiencing droughts (CENAPRED, 2014). While the belt mainly covers the central and northern parts of Mexico, large droughts can affect more regions, generating widespread disruptions to economic activity throughout the country. For instance, the last two largest droughts affected, in different degrees and intensities, 85% and 76% of the country.[7] To better identify the drought's magnitude, the Drought Monitor of CONAGUA classifies municipalities into five categories based on the intensity of the drought, ranging from D0 to D4, similar to the methodology of the United States Drought Monitor.[8] Throughout the analysis, we use D3 and D4 categories to focus only on extreme droughts, which are the most disruptive for the economic activity, using data from 2016 to 2024.

Evidence of dryness effects on economic activity and employment

The adverse effects of droughts can be particularly disruptive for economic sectors that use large quantities of water as part of their productive processes, also known as water-intensive sectors. Among this group of sectors, agriculture stands out by using 67% of the water, much more than the rest of the economic sectors and the urban use by the general population.[9] Droughts can disrupt agricultural production by increasing costs of key inputs (water), or expanding the distribution and incidence of pests and diseases, primarily affecting specialty

[7] The last two largest droughts hit the country in 2011 and 2024. For more details, please see: Multi-year drought and heat waves across Mexico in 2024 | NOAA Climate.gov

[8] This Monitor identifies municipalities experiencing droughts and classifies them by severity every two weeks on a scale ranging from abnormally dry (D0), moderate droughts (D1), severe droughts (D2), extreme droughts (D3), to exceptional droughts (D4). Thresholds are determined based on quantitative measures such as precipitation, streamflow, reservoir levels, temperature, evaporative demand, soil moisture, and vegetation health.

[9] Other uses of water include: urban 14.7%, power generation 4.6%, and industrial 3.1%. For more details, please see: Usos del agua (conagua.gob.mx)

crops, which are the ones with higher value per unit of input, further magnifying the adverse effects of droughts (Leng & Hall, 2019; Nguyen et al., 2023).[10]

We start by verifying that droughts actually disrupt agricultural production and agricultural yields (measured as the production per hectare) using annual data at the municipal level from SIAP. In the estimation, we use information on the 64 most important crops in Mexico, which represent approximately 90% of the total agricultural production in the country.[11] As presented in Table 1, our findings are consistent with previous literature in Mexico that shows that, indeed, regions subject to extreme drought experience a significant reduction both in agricultural production and yield (Sutanto et al., 2024).

Lower levels of production can lead to lower revenues for firms, which may, in turn, translate into lower employment levels, especially in regions where agricultural jobs represent a significant share of the employed population. In Mexico, the agricultural sector employs 11.3% of the total number of workers, making it one of the most important sectors in terms of employment.[12] We use this number as the threshold to classify municipalities as non-agricultural and agriculturally intensive, expecting to find larger effects on the latter group. Municipalities with a greater concentration of agricultural labor cannot only be directly affected by the decreased access to water, but these regions often have lower income levels and are less developed, potentially making them more vulnerable to the adverse effects of droughts through general equilibrium effects from a reduction in local aggregate demand.

We test the effects of droughts on employment using publicly available data at the municipal level on the total number of employees reporting formal wages to IMSS. We estimate the effects on total employment as well as the employment in agricultural and non-agricultural intensive regions to verify that the effects are more pronounced in agricultural municipalities. As presented in Table 2, our findings reveal that regions hit by extreme droughts experience a significant decline in employment levels. Consistent with a larger

[10] For more details, please see: Drought and Agricultural Impacts | Drought.gov
[11] SIAP data also includes information on the rest of crops, but the availability over time of that data is intermittent.
[12] The national average is calculated using the National Survey of Occupation and Employment (ENOE).

disruption of water-intensive sectors and general equilibrium effects, this decline is only driven by an employment reduction in agricultural municipalities.

Use of financing tools in Mexico to cope with income shocks

To cope with the income disruption, individuals may use their available financing tools. However, the number and availability of these tools may be lower for individuals living in middle-income economies, such as Mexico. Unlike in high-income economies, individuals in these countries have weaker government support, which can make a significant difference in coping with financial distress. For instance, Deryugina (2017) finds that non-disaster government transfers, such as unemployment insurance, exceed those of direct disaster aid in the United States, implying that victims in high-income economies are better insured against natural disasters than previously thought. Moreover, insurance markets in middle-income economies are largely missing (Swiss Re, 2024), which can lead to different outcomes when coping with a financial shock.[13] For instance, Gallagher & Hartley (2017) find that lower debt levels after Hurricane Katrina are explained by homeowners using flood insurance to repay their mortgages rather than to rebuild.

Mexico is not the exception among middle-income economies; the country's insurance penetration is very low, and there is a lack of non-disaster government support.[14] In this context, individuals may rely on other financing tools such as credit cards (revolving credit), other credit (non-revolving credit), own resources—liquid savings—, or their social safety net—for instance via remittances—. The National Survey on Financial Inclusion (ENIF) provides a comprehensive overview of the financial instruments used by individuals in Mexico. According to the most recent wave of the survey in 2023, 64.2% of respondents report having some form of savings. However, the majority of these savings are limited in size and held through informal channels. Access to credit is similarly constrained: the most commonly held formal credit instrument is the credit card, reported by 28.6% of respondents, followed by non-revolving low-quality credit products (7.2%) and high-quality credit (4.5%).

[13] Only 4 middle-income economies are part of the world's 20 largest insurance markets by nominal premium volumes, Mexico is ranked 18th with a global market share of 0.6%. For more details, please see: sigma-2-2024-life-annuity-insurance.pdf (swissre.com)

[14] In Mexico, only 22.9% of people have any type of insurance, and most of them have either life or car insurance that are unlikely to be affected by dryness. For more details, please see: Encuesta Nacional de Inclusión Financiera (ENIF) 2024. Principales resultados. (inegi.org.mx)

Remittances also play a significant role in household finances. Approximately 10.4% of respondents report supplementing their income with transfers from abroad. These remittances can serve as a buffer against local economic shocks, particularly because senders—residing outside the country—are not themselves exposed to domestic disruptions.

Moreover, according to ENIF, a substantial share of households face difficulties meeting their monthly expenses. In fact, 40% of respondents reported being unable to cover their spending needs at some point during 2023. In response, households declare to have used a variety of financial tools, as reported in Appendix Table A1. Specifically, 51% relied on family or friends for support—a figure that rises to 58% among those receiving remittances, which in the analysis we use as proxy for support from social safety nets. Additionally, 42% turned to their savings, which we capture in the analysis using deposits data as further described in the next sections.

In terms of credit tools, 11% of respondents used credit cards or other types of credit to cope with the shortfall (ENIF does not distinguish here by credit types). Among those who already possess a credit card, reliance on this tool increases to 31%. In contrast, only 23% of individuals with access to other forms of credit utilized them in these situations. Financial distress is also associated with increased credit delinquency: 9% of respondents reported falling behind on loan payments. This rate is significantly higher among those who hold credit cards (16%) or other credit products (20%). Finally, despite using various financial strategies, 69% of respondents reported reducing their expenditures in response to financial strain. This widespread reduction in consumption suggests that, in the Mexican context, access to financial tools that enable effective consumption smoothing remains limited—even among those with access to formal credit.

Availability of financing tools across population groups

The use of financing tools in Mexico to cope with income shocks caused by droughts can vary based on the availability of these tools between population groups. While ENIF provides insightful information on the use of financing tools, it is not designed to provide additional information on access by socioeconomic groups or in-depth information on more nuanced tools, such as different credit types. Thus, to study this question, we exploit several additional data sources containing detailed administrative information on the universe of different

financing tools, which are described in detail in the next section and are used later on to analyze the causal effects of droughts. The data includes: (i) Bank deposits as proxy of individuals' own liquid savings; (ii) Remittances as proxy of family or friends´ support; and (iii) Extremely detailed data on credit that allow us to distinguish between revolving (credit card loans) and different types of non-revolving consumer credit and their underlying credit conditions. In this section, we provide a snapshot of the availability and conditions of these financing tools across population groups.

Tables 3 and 4 characterize the availability of financial tools across the population with different poverty levels. Table 3 Column (1) shows the number of municipalities with positive values of each variable (population, different credit types, savings, and remittances), and Columns (2)-(5) divide municipalities into four groups (quartiles) of equal population size based on the poverty levels in 2015.[15] As presented in Table 3, individuals living in regions with lower poverty levels have more access to financing tools, with 70.2% of revolving credit—aggregated sum of credit card lines—65.3% of non-revolving consumer credit—outstanding amount—, and 82.4% of savings.[16] In contrast, individuals living in regions with higher poverty levels only have slightly greater access to remittances, with 53.9% of the total.

Moreover, individuals living in regions with lower poverty levels access credit with better borrowing conditions. As presented in Table 4, the number of loans in these regions is much larger, their interest rate is lower, and the loan amounts are greater than those of loans in regions with higher poverty levels. Taken together, these findings indicate potential heterogeneous responses in coping with a financial shock, where individuals in already vulnerable regions have fewer available financing tools and worse borrowing conditions.

Among credit tools, credit card loans are the most widespread type of consumer credit in terms of the number of cards and the outstanding credit, which is the aggregated sum of credit lines. However, individuals face a tradeoff when using credit card loans to cope with

[15] If financial tools were evenly distributed across municipalities, each group would receive 25% of the total, reflecting their population share.

[16] Appendix Table A2 shows the distribution of credit financing tools in terms of number of loans and credit card loans. When looking at that dimension, the distribution of tools between municipalities with lower and greater share of population in poverty is slightly more even than when comparing the total outstanding amount.

a financial shock. On the one hand, credit cards have pre-approved credit lines that individuals can use as needed, unlike non-revolving credit, which requires a special creditworthiness assessment every time it is granted. This is an important distinction because, in economies with shallow credit markets such as Mexico, financial intermediaries often do not respond to liquidity demands of individuals with short credit histories and no assets to pledge as collateral, and droughts can magnify the informational asymmetries faced by already credit constrained individuals—such as the ones living in regions with higher poverty levels—. On the other hand, these pre-approved credit lines are relatively more expensive than non-revolving credit, with an average interest rate of 51.9%, compared to 50.1% and 22.8% of low-quality and high-quality non-revolving loans, as presented in Table 4.

Despite the high presence of consumer credit across municipalities, some individuals may substitute credit or combine its use with other tools, such as their own liquid savings, or make use of their social safety net to cope with a financial shock. We use deposits as a proxy of liquid personal savings, and remittances as a proxy of informal social support from the individual's safety net. In Mexico—as in many other middle-income economies—remittances are an important source of income, reaching almost all municipalities and representing 4 percent of the country's GDP (CONAPO & Fundación BBVA, 2024). In fact, remittances are the most evenly available financing tool between groups of municipalities, as presented in Table 3.

The combination of credit with other financing tools is also important because it allows individuals to avoid relying completely on credit, especially as the most available credit type—credit cards—is characterized by having high interest rates, which increases the probability of defaulting on loans if overused after a financial shock. Loan defaults can have longer-term consequences, as they are part of the individual's credit history and their record is kept in the credit bureau for up to six years, affecting future access to credit. In Mexico, own estimations indicate that individuals who default on consumer credit are 20% less likely to obtain a new loan in the following year compared to those who have not defaulted. Moreover, those who manage to secure a new loan face higher interest rates (approximately 8 percentage points more) and receive lower loan amounts (14% reduction).

III. Data

This paper leverages information from several data sources. To assess how individuals use financing tools after a drought, we rely on consumer credit data—credit card loans and non-revolving credit—, own resources—deposits used as a proxy of liquid savings—, and the individual's social safety net—remittances data—. To identify the intensity and location of droughts, we use information from the Drought Monitor. For additional analysis, we use socioeconomic data from other publicly available sources and exploit the granularity and variety of our financing tools data to conduct a comprehensive analysis of the heterogeneities and underlying mechanisms of our results.

Credit Card Loans

To study the use of consumer credit financing tools, we use credit card loans data.[17] Credit cards are the most important consumer credit type in Mexico both in terms of number of loans and outstanding credit, with over 30 million cards and over 420 million pesos in outstanding credit in April 2024.[18] We exploit a proprietary dataset containing information on the universe of credit card loans issued by commercial banks.[19] This dataset contains bimonthly information from 2016 to 2024 with information at the municipality-bank-gender-age level, referred to as "cells" henceforth.

Since 2022, the dataset was expanded with additional information on credit characteristics at the cell level, such as the weighted interest rate and the average credit line limit. As a whole, this dataset allows us to identify loans for which the borrower was not able to meet the loan's obligations (i.e., non-performing loans), distinguish between men and women customers, identify their municipality, the size of the credit line, and its underlying interest rate.

[17] The term credit card loans implies that more than one credit card could be associated with the same loan.
[18] The second most important credit type are salary-based loans with over 280 million pesos in outstanding credit, 33% less than credit card loans.
[19] Other institutions such as retail stores also grant credit cards; however, they represent a small share of the total outstanding credit in the Mexican market.

Non-revolving consumer credit

To expand our analysis on the use of credit after a drought, we use non-revolving consumer credit data. Non-revolving consumer credit is composed of four main segments, including: salary-based, automotive, personal, and consumer-durable loans that we group up based on their financing conditions. We call the first two "high-quality" loans for having better credit conditions, as they are typically associated with the formal economy, requiring proof of income, and the payments can be directly debited from the borrower's payroll account. In contrast, we call the latter two "low-quality" for having worse borrowing conditions, meaning higher interest rates, lower amounts, and shorter maturities, as they are easy access loans that do not require specific documentation, such as proof of income, for their approval. This data comes from a proprietary dataset containing information on the universe of non-revolving consumer credit issued by commercial banks. The data is reported bimonthly at the loan level, but we aggregate it up to the cell level to match our data on credit card loans.

Remittances and Deposits

We use deposits and remittances data to assess whether individuals make use of other financing options to cope with the adverse economic effects of droughts. We use deposit data as a proxy of the individual's own resources—savings—, and remittance data as a proxy of the individual's social safety net. Deposits data is reported by the National Banking and Securities Commission (CNBV). This dataset contains publicly available data on monthly bank deposits at the municipal level. Remittance data is reported by Banco de México. This dataset is composed of quarterly data at the municipal level. As remittance data is reported in US dollars, we convert it to Mexican pesos using the monthly average FIX exchange rate also reported by Banco de México.

Droughts

As previously introduced in Section II, to identify droughts and their location and intensity, we use publicly available data from the Drought Monitor of the National Commission of Water (CONAGUA), a decentralized agency of the Mexican Ministry of Environment and Natural Resources (SEMARNAT). This Monitor identifies municipalities experiencing droughts and classifies them by severity every two weeks on a scale ranging from abnormally

dry (D0), moderate droughts (D1), severe droughts (D2), extreme droughts (D3), to exceptional droughts (D4). The categorization follows the methodology of the U.S. Drought Monitor, where thresholds are determined based on quantitative measures such as precipitation, streamflow, reservoir levels, temperature, evaporative demand, soil moisture, and vegetation health.[20]

In our analysis, we focus on extreme and exceptional droughts (D3 and D4), as these droughts may be the ones that generate the strongest disruptions to economic activity. In doing so, we first aggregate the number of weeks municipalities in our dataset were hit by D3 and D4 droughts, and then add them up over one-year windows. Thus, our variable of interest captures the cumulative effects of droughts over time (which is important as droughts are chronic, not acute, weather shocks), and minimizes the potential biases stemming from seasonal variations in drought patterns. Finally, we collapse the droughts' biweekly data to bimesters starting in 2016 to match it with our credit card loans and non-revolving credit proprietary datasets.

Socioeconomic Characteristics

We use socioeconomic data to analyze heterogeneous effects in the sample that help in the understanding of the main results. Specifically, we use socioeconomic characteristics such as poverty, labor formality, and years of schooling to assess whether drought-related effects vary by preexisting vulnerability conditions. Poverty data is from 2010 and comes from the National Council for the Evaluation of Social Development Policy (CONEVAL). CONEVAL follows a multidimensional definition of poverty, that requires an individual to have an income below the poverty line and at least one social vulnerability, measured through six binary indicators: educational lag, lack of access to healthcare services, social security, housing quality and space, basic services in housing, and adequate food. Labor informality and years of schooling come from the 2010 Mexican Census reported by the National Institute of Statistics and Geography (INEGI).

[20] However, this is not a purely statistical model; it also incorporates qualitative assessments. The methodology synthesizes multiple indices, forecasts, and local impacts to produce an evaluation that best represents current drought conditions.

Summary statistics

Table 5 presents the summary statistics of the key variables used in the analysis for each of the datasets. The Table shows the statistics of the total sample and two sub-samples of interest following the same division as presented in Table 2: agricultural and non-agricultural municipalities, as the negative effects of water scarcity may be more pronounced on the first group of municipalities. We divide the sample based on the percentage of agricultural employment in a given municipality, with a municipality defined as agricultural if its share of agricultural employment is greater than the national average of 11.3%.

In terms of credit characteristics, we find that agricultural municipalities have worse credit access and riskier credit profiles than non-agricultural municipalities. Regardless of the credit tool—credit card loans, low-quality or high-quality non-revolving credit—agricultural municipalities have lower total outstanding credit and fewer loans or cards, but higher delinquency rates. For credit card loans, agricultural municipalities have statistically significantly worse borrowing conditions with higher interest rates and smaller and more saturated credit lines. For other financing tools, agricultural municipalities have lower deposits per capita, but, contrary to credit and deposits, these regions have more access to remittances per capita. In terms of exposure to droughts, we find that agricultural municipalities are slightly more exposed to moderate and extreme droughts than their non-agricultural counterparts. Finally, agricultural municipalities have a greater portion of their population with socioeconomic vulnerabilities, meaning a greater share living under the poverty line, with only basic education, and working in informal jobs.

IV. Empirical strategy

Our empirical strategy aims to study the use of different financing tools after an exogenous drought. We estimate the effects of droughts using the cumulative number of weeks any given region has been exposed to extreme droughts in the last year. This allows us to capture the contemporary and lagged exposure, which is important as droughts are chronic, not acute, weather shocks. For each financing tool, we estimate slight variations of the same empirical specification depending on the level of aggregation and periodicity of each dataset. As all consumer credit datasets—credit card loans, high-quality and low-quality non-revolving—

share the same aggregation and periodicity, we use the following specification as our baseline:

$$y_{m,g,e,b,t} = \alpha + \beta X_{m,t} + \mu_{m,g,e,b,t} + \mu_{b,t} + \mu_{year,m} + \mu_{month,m} + \varepsilon_{m,g,a,b,t}, \qquad (1)$$

where the outcome variable $y_{m,g,e,b,t}$ represents a credit outcome in municipality (m), bank (b), gender (g), age (a), at time (t), which for the case of consumer credit is defined as bimonthly periods. The credit outcome could be the delinquency rate, built as the ratio of non-performing loans and total outstanding credit, performing loans, non-performing loans, total outstanding credit, and the number of loans or credit card loans. Our variable of interest $X_{m,t}$ is the number of weeks of extreme droughts in municipality (m) over the last year. Thus, the coefficient of interest (β) measures the effects of every 10 weeks of exposure to extreme droughts during the contemporaneous bimester and on each of the previous five bimesters.

For a causal interpretation of our coefficient of interest, the identifying assumption requires that the droughts' exposure in a region is not associated with unobserved factors that could potentially affect the individuals' use of financing tools in the same region. We address this by saturating our regression with different combinations of fixed-effects. We include municipality-bank-gender-age $\mu_{m,g,e,b,t}$ fixed-effects to control for time-invariant heterogeneity, such as bank strategies for each credit market group. The bank-bimester $\mu_{b,t}$ fixed-effects allow to control for the entries and exits of banks from the sample, as well as for bank-specific policies across municipality-gender-age groups. Finally, we control for regions' baseline climate conditions in each season with municipality-month $\mu_{month,m}$ fixed-effects, for region-specific nonlinear trends with municipality-year $\mu_{year,m}$ fixed-effects, and for common shocks to all municipalities with time fixed-effects.

After controlling for seasonality and time trends specific to each municipality, any residual difference in weeks of extreme droughts can be considered unexpected and, consequently, exogenous to other time-varying factors that could affect credit delinquency. This way, the exploited variation is the difference in the number of weeks with extreme drought with respect to the municipality-monthly specific historical averages, after controlling for nonlinear trends specific to each municipality. Finally, while the empirical specifications of deposits and remittances have slight changes due to the different granularity

and periodicity of their respective datasets, all specifications control for seasonality and time trends specific to each municipality, allowing a causal interpretation of our results. The variations from the baseline equation (1) presented above are introduced as needed in the following Section.

V. Results

Credit card loans

We start our analysis by exploring the use of credit card loans after a drought. First, we estimate the impact of unusual extreme droughts on credit delinquency rates, saturating the specification with an increasing set of fixed-effects that capture within-bank, within-municipality, borrower-specific, and seasonal variation to test the robustness of the results. As shown in Table 6, regardless of the specification, the magnitude of the point estimate remains stable. In the most saturated specification (column 5), results show that, for every ten weeks of exposure to extreme droughts over a one-year window, the credit card loans' delinquency rate rises by around 0.10 percentage points, which represents 1.6 percent of the mean delinquency rate in the sample as reported in Table 5 (6.1%). We use this specification as our preferred one because it includes seasonality and time trends specific to each municipality on top of the rest of the fixed-effects, allowing us to claim that any residual difference in weeks of extreme droughts can be considered unexpected and, consequently, exogenous to other time-varying factors that could affect credit delinquency. Henceforth, we use that specification for the rest of the results presented in this section.

Since the delinquency rate is built as the ratio of non-performing loans to total outstanding credit, we break down the delinquency rate to assess whether the increase presented in Table 6 is driven by changes in performing or non-performing credit. We also test the extensive margin using the number of credit card loans to assess whether the number of cards in the system increases after a drought. For these estimations, we look both at the entire sample, and the disaggregation between agricultural and non-agricultural municipalities to test whether the effects are more concentrated on the group of water-intensive regions, similar to the estimations on employment presented in Table 2.

Table 7 presents the effects on performing loans, non-performing loans, total outstanding credit, and the number of credit card loans for every 10 weeks of droughts.[21] When looking at the full sample, our findings reveal that changes in credit delinquency are only explained by non-performing loans, which shows a statistically significant increase of 2.9%. Moreover, this increase is only explained by an increase in non-performing loans concentrated in agricultural-intensive municipalities (4.1%), consistent with the hypothesis of a larger disruption of water-intensive sectors and general equilibrium effects. For these municipalities, delinquency rates increase by 0.128 percentage points (2% of the sample mean) for every 10 weeks of unusual droughts.

For the extensive margin, we find no uptakes in the number of credit card loans after a drought (column 5). On the contrary, we find a small statistically significant decline of 0.1% in the number of cards when using the full sample, and no statistically significant changes in the subsamples. Taken together, these findings suggest that the exposure to droughts harmed the ability of individuals to repay their loans, increasing credit default, while the lack of changes in the number of new credit card loans is in line with the lack of response of financial intermediaries to liquidity demands that require a special granting assessment after a shock.[22] Drought-related liquidity problems could vary based on individual characteristics. For instance, as presented in Tables 3 and 4, individuals living in regions with higher levels of poverty have lower access to financing tools, and those with access have worse credit conditions than individuals in regions with less poverty. Also, these individuals could be the first affected with lower employment levels, consistent with the idea that lower-skilled individuals lose their jobs first in times of economic downturns (Kugler et al., 2023). We explore these dimensions by dividing the sample of agricultural-intensive municipalities—those that concentrate the increase in delinquency rates and non-performing loans—based on socioeconomic characteristics.

[21] We conduct a horse-race model between moderate (D0-D2 categories) and extreme droughts (D3 and D4) and find that the increase in non-performing credit and delinquency rates is mainly driven by the exposure to extreme droughts. These results can be found in Appendix Table A3.

[22] The lack of effect on performing credit in our analysis for the average bimester could be hindering different individual responses based on seasonal spending obligations, such as end-of-year expenses. We further explore if this is the case later in this section when analyzing seasonality effects.

Table 8 presents the effects of dryness on credit card loans by socioeconomic characteristics. Specifically, we divide the sample based on median labor informality, education, and poverty levels of the municipalities in our sample. Our findings confirm that the adverse effects of droughts are more pronounced for individuals living in more vulnerable regions. Individuals living in regions with lower education levels, more poverty, and higher levels of labor informality show a statistically significant increase in non-performing loans, which drives an increase in the delinquency rate of those regions, given the lack of statistically significant changes in performing loans. For instance, individuals living in regions with higher poverty increase their non-performing loans by 8.2%, which leads to a large and statistically significant increase in the delinquency rate of 0.328 percentage points (5.1% of the sample mean).

These worse socioeconomic characteristics also translate to more binding borrowing conditions, as previously introduced in Table 4. Individuals in more vulnerable regions often face higher information asymmetries and have fewer assets to pledge as collateral, further constraining their financing options. We explore this hypothesis by dividing the sample of agricultural-intensive municipalities based on credit conditions in 2022: interest rate, credit line size, and absolute distance to the credit card limit to measure the saturation of credit lines.[23] Consistent with our hypothesis, the findings reveal that the adverse effects of droughts are concentrated only on individuals with the worst credit conditions. Individuals granted credit card loans with higher interest rates, lower credit card lines, and more saturated lines increase their non-performing loans and, consequently, their delinquency rates after a drought. For instance, individuals with higher interest rates increase their non-performing loans by 4.1%, which leads to a statistically significant increase in the delinquency rate of 0.221 percentage points (3.4% of the sample mean). These findings suggest that the worse borrowing conditions make it harder for these individuals to repay their credit obligations in times of financial distress.

[23] We use the year 2022 to split the cells because it is the first year for which this information is available. In Appendix Table A4, we show that there is a high overlap between the group of individuals with worse credit conditions—higher interest rates, smaller and more saturated credit lines—and the group of more vulnerable individuals by socioeconomic characteristics—living in more informal, poorer, and more illiterate regions.

Non-revolving credit and other financing tools

Individuals in exposed regions can also use other financing tools instead. One alternative is other credit tools, such as non-revolving consumer credit, which, contrary to the pre-approved revolving lines of credit card loans, requires a special creditworthiness assessment each time it is granted. We estimate the same specifications presented in Table 7 for non-revolving credit using the full sample of loans, as well as the division between low-quality and high-quality loans. As previously explained, the categorization of non-revolving loans by quality is based on their underlying credit conditions. Thus, this division represents an equivalent division of loans based on credit conditions as the one presented in Table 9 for credit card loans.

Table 10 presents the effects on performing loans, non-performing loans, total outstanding credit, and the number of loans for every 10-weeks of droughts. Contrary to the results for credit card loans, we find statistically significant increases in the performing credit, total outstanding amount, and number of loans, and these increases are concentrated only in the groups of high-quality loans. Specifically, we find a statistically significant uptake of 1.6 percent in performing credit, which drives up the total outstanding credit by 1.3 percent. Lined up with these results, in the extensive margin, we find a statistically significant increase of 0.4 percent in the number of loans.

We find no statistically significant changes in either the intensive margin or the extensive margin for the total sample of non-revolving credit and for the sample of low-quality loans. When bringing together these results with the ones of Table 9 for credit card loans, these findings imply that there is a group of individuals who can access non-revolving credit with the best borrowing conditions after a drought without negative effects on credit delinquency, and there is another group of individuals in exposed regions that do not (or cannot) access these loans to cope with financial distress. On the contrary, this latter group seems to be more credit-constrained due to their worse socioeconomic characteristics and their worse credit conditions.

Some individuals in agricultural-intensive regions may also turn to non-credit financial tools to cope with the shock. First, we study the role of deposits, which we use as a proxy for liquid personal savings. In columns 1 and 2 of Table 11, we study the effect of

drought on deposits for agriculture and non-agriculture municipalities. Our findings show a statistically significant decline of 3.8 percent in deposits in agricultural-intensive regions and no effect in non-agriculture regions. This finding is consistent with our previous results, indicating that these regions are the most affected by the shock. It also shows that individuals make use of savings to cope with the drought-related financial shock, consistent with the use of their own savings when they are unable to cover their expenses with their labor income (as reported by ENIF in Section 2). Moreover, we find evidence that, in doing so, individuals in some exposed regions can rely on savings to avoid defaulting on their existing credit card loans (columns 3 and 4 of Table 11). Our findings reveal that credit card loans' delinquency increases only 0.09 percentage points in agricultural-intensive municipalities with a greater savings per capita, much less than the 0.25 percentage points increase in exposed municipalities with a lower per capita availability of deposits to cope with the shock.

We also explore whether individuals in exposed regions use remittances, which we use as a proxy of support from the individuals' social safety net. As in the case of deposits, columns 1 and 2 of Table 12 show the effect of drought on remittances for agriculture and non-agriculture municipalities. Our findings show a statistically significant increase in remittances both in agricultural and non-agricultural intensive regions. However, the 16.3% increase in the agricultural regions is much larger than the 5.5% uptake of non-agricultural regions. Moreover, aligned with the use of savings, we find evidence that individuals in agricultural regions use remittances to cover their existing debts and avoid credit default, such as in (Heres et al., 2022). Our findings reveal that agricultural-intensive municipalities with greater remittance per capita do not experience a statistically significant increase in credit card loans' delinquency after a drought. In contrast, individuals in agricultural intensive municipalities with lower remittances per capita show a statistically significant rise of 0.29 percentage points in their delinquency rate (columns 3 and 4 of Table 12).

Taken together, the results on high-quality credit, deposits, and remittances indicate that some individuals in Mexico use a variety of financial tools to cope with droughts. Nonetheless, other individuals might not have access to these tools, and the income shock caused by droughts leads them to credit card default. But before defaulting on these loans, a question remains if they increase the balance in specific periods where they are more liquidity

constrained due to seasonal spending obligations. We explore this in detail in the following sub-section.

Seasonal behavior

We break down the periodicity of the analysis to explore potential heterogeneous individual responses based on seasonal spending obligations. For instance, Figure 1 shows that performing credit card transactions peak by the end of the year, with performing credit in December 9.9% above the annual mean. This seasonal use of credit could be explained by the end-of-year financial commitments, such as the holidays and family gatherings, which demand individuals' higher levels of liquidity. To do so, we break down the analysis by bimester—the maximum granularity allowed by our credit datasets—to explore seasonal variations in the use of credit card loans and non-revolving consumer credit.

Table 13 presents the results on the seasonal effects of credit card loans. In line with the rise in liquidity needs during the holiday season, we find a statistically significant increase in performing loans that peaks in December with an increase of 1.3%. This uptake lines up with a statistically significant increase of 1.5% in total outstanding credit, and a 0.3% increase in the number of credit card loans. However, this surge in credit use is followed by a rise in the delinquency rate two bimesters later, reflecting the 90-day threshold for a loan to be classified as delinquent. This pattern suggests that some individuals also use credit card loans to cope with dryness, but only during times of higher liquidity constraints, and it ultimately leads to credit default a few months later.

When running the same seasonality analysis for the case of non-revolving loans, we also find a statistically significant increase in performing loans, but it is two months later than December and of smaller magnitude than revolving credit (Panels A and B in Table 14). This finding is consistent with a lagged response and lower loan amounts for non-revolving credit due to the need for credit approval each time it is requested. As in the case of revolving loans, this increase in credit leads to default two bimesters later. When we split the sample of non-revolving credit into high and low quality, we find that the increase in performing loans at the beginning of the year and the uptake in non-performing loans a few months later is only driven by low-quality credit (Panels C and D in Table 14). This indicates that some individuals also rely on this expensive credit type to cope with the shock and, as in the case

of credit card loans, ultimately leads to credit default. In the case of high-quality credit, we find an increase in performing loans at the end of the year, but individuals accessing these better credit conditions do not end up defaulting on their debt (Panels E and F in Table 14).

Now, we explore in more detail the characteristics of the group of individuals who are driving this increase in performing credit card loans that eventually leads to default. In doing so, we restrict the analysis to the last bimester of the year—when we find the largest uptake of performing loans—and divide the sample based on credit conditions, such as the ones previously presented in Table 9. As presented in Table 15, our findings show that individuals in agricultural-intensive regions with the worst credit conditions are the ones driving this uptake in performing loans. For instance, the group of individuals charged with higher interest rates increases their performing credit by 3%, while the group charged lower rates shows no statistically significant changes in their use of credit.

Finally, to fully understand the relationship between credit card loans' use and other financial tools, we explore whether individuals living in regions where credit card loans are not used also coincide with higher use of savings (deposits) and remittances. To do so, in Table 16 we split the municipalities in the sample based on their average credit card loans' conditions in 2022 (interest rate, credit limit, and distance to credit limit) to estimate the use of these tools as substitutes for increasing credit card debt. To maintain consistency with the previous analysis for credit card that uses only December, we also run an annual regression taking as dependent variables the stock of deposits in December and the cumulative remittances received during a calendar year. Our findings reveal that individuals with the best borrowing conditions for credit card loans are the ones with the largest use of remittances and deposits after a drought. For instance, in regions where credit card loans have lower interest rates, there is a 5.3% decline in deposits in December due to droughts, while in regions where individuals are charged higher interest rates for their credit card loans, there are no changes in deposits.

Taken together, these findings reinforce the story of the existence of one group composed of individuals who can access credit under better borrowing conditions and make use of other financing tools, such as savings and remittances, to avoid default in periods of financial distress. In contrast, there is a group of more vulnerable individuals with worse

socioeconomic characteristics who only have access to credit with the worst credit conditions. Their access is limited to credit card loans and, to a lesser extent, to low-quality loans, options that are widely available but come with the most unfavorable terms. This group relies on these costly credit lines to cope with droughts, often resulting in loan defaults and further exclusion from the credit market.

VI. Conclusions

In this paper, we study how individuals make use of different financing tools after a drought. We exploit the exogenous variation from unusual extreme droughts to assess the individuals' behavior using credit card loans, non-revolving consumer credit, savings, and remittances data from Mexico. To our knowledge, this is the first paper that explores the use of financing tools after a drought, which is becoming increasingly important to understand, as droughts can increase in frequency and intensity going forward due to higher global temperatures associated with climate change, and individuals have differential access to financing tools.

Our findings clearly show marked heterogeneous responses summarized in two groups of individuals based on their availability and borrowing conditions of the tools they access. The first group lives in less vulnerable regions with better education and higher levels of formal employment, having access to credit card loans and non-revolving credit with the best borrowing conditions, and using their savings and remittances to avoid default. This combination of access to financing tools and borrowing conditions makes them well-prepared to face financial shocks, such as the ones generated by droughts.

In contrast, the second group comprises individuals from more vulnerable regions and higher levels of labor informality, which limits their access to high-quality non-revolving credit or liquid savings in periods of financial distress. They mostly have access to credit card loans—the most widespread form of consumer credit—which offer pre-approved revolving lines but under worse terms than those available to more resilient individuals. We find evidence that individuals in the second group tend to rely on these costly credit lines, especially in times of the year that demand individuals' higher levels of liquidity, which increases their likelihood of default later on.

Finally, our findings shed light on the need for public policies aimed at mitigating the adverse effects of droughts on individuals. Post-disaster recovery policies are usually successful at targeting acute disasters—such as earthquakes, hurricanes, or floods— but face more challenges when tackling more prolonged disasters with fuzzier start and end dates, such as droughts. For droughts, traditional post-disaster policies have focused on firms, especially those that belong to the agricultural sector, either facilitating credit access or improving infrastructure for future production. While helping firms is important, our findings show that individuals also need post-drought recovery policies as droughts can lead to credit default, harming future access to credit and becoming poverty traps for already vulnerable individuals.

References

Afridi, F., Mahajan, K., & Sangwan, N. (2022). The gendered effects of droughts: Production shocks and labor response in agriculture. *Labour Economics*, *78*, 102227. https://doi.org/10.1016/j.labeco.2022.102227

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. https://doi.org/10.1016/j.jdeveco.2023.103246

Baez, J., Caruso, G., Mueller, V., & Niu, C. (2017). Heat Exposure and Youth Migration in Central America and the Caribbean. *American Economic Review*, *107*(5), 446–450. https://doi.org/10.1257/aer.p20171053

Berg, G., & Schrader, J. (2012). Access to credit, natural disasters, and relationship lending. *Journal of Financial Intermediation*, *21*(4), 549–568. https://doi.org/10.1016/j.jfi.2012.05.003

Brown, J. R., Gustafson, M. T., & Ivanov, I. T. (2021). Weathering Cash Flow Shocks. *The Journal of Finance*, *76*(4), 1731–1772. https://doi.org/10.1111/jofi.13024

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*(7577), 235–239. https://doi.org/10.1038/nature15725

CENAPRED. (2014). *Serie de Fascículos: Sequías* (Versión electrónica). Secretaría de Gobernación. https://www.gob.mx/cenapred/documentos/serie-de-fasciculos-sequias

Collier, B. L., Haughwout, A. F., Kunreuther, H. C., & Michel-Kerjan, E. O. (2020). Firms' Management of Infrequent Shocks. *Journal of Money, Credit and Banking*, *52*(6), 1329–1359. https://doi.org/10.1111/jmcb.12674

CONAPO, & Fundación BBVA. (2024). *Anuario de Migración y Remesas México*. https://www.gob.mx/conapo/documentos/anuario-de-migracion-y-remesas-mexico-yearbook-of-migration-and-remittances-mexico

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95. https://doi.org/10.1257/mac.4.3.66

Deryugina, T. (2017). The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance. *American Economic Journal: Economic Policy*, *9*(3), 168–198. https://doi.org/10.1257/pol.20140296

Deryugina, T., Kawano, L., & Levitt, S. (2018). The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns. *American Economic Journal: Applied Economics*, *10*(2), 202–233. https://doi.org/10.1257/app.20160307

Dobridge, C. L. (2018). High-Cost Credit and Consumption Smoothing. *Journal of Money, Credit and Banking*, *50*(2–3), 407–433. https://doi.org/10.1111/jmcb.12465

Gallagher, J. (2014). Learning about an Infrequent Event: Evidence from Flood Insurance Take-Up in the United States. *American Economic Journal: Applied Economics*, *6*(3), 206–233. https://doi.org/10.1257/app.6.3.206

Gallagher, J., & Hartley, D. (2017). Household Finance after a Natural Disaster: The Case of Hurricane Katrina. *American Economic Journal: Economic Policy*, *9*(3), 199–228. https://doi.org/10.1257/pol.20140273

Heres, D., Jaume, D., Tellez de la Vega, E., & Tobal, M. (2022). *Do Remittances Complement or Substitute for Consumer Credit? The Relevance of Heterogeneous Effects in the Mexican Context* (SSRN Scholarly Paper 4189160). Social Science Research Network. https://doi.org/10.2139/ssrn.4189160

IPCC (Ed.). (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. https://doi.org/10.1017/9781009157896

Jessoe, K., Manning, D. T., & Taylor, J. E. (2018). Climate Change and Labour Allocation in Rural Mexico: Evidence from Annual Fluctuations in Weather. *The Economic Journal*, *128*(608), 230–261. https://doi.org/10.1111/ecoj.12448

Kugler, M., Viollaz, M., Duque, D., Gaddis, I., Newhouse, D., Palacios-Lopez, A., & Weber, M. (2023). How did the COVID-19 crisis affect different types of workers in the developing world? *World Development*, *170*, 106331. https://doi.org/10.1016/j.worlddev.2023.106331

Kuwayama, Y., Thompson, A., Bernknopf, R., Zaitchik, B., & Vail, P. (2019). Estimating the Impact of Drought on Agriculture Using the U.S. Drought Monitor. *American Journal of Agricultural Economics*, *101*(1), 193–210. https://doi.org/10.1093/ajae/aay037

Leeper, R. D., Bilotta, R., Petersen, B., Stiles, C. J., Heim, R., Fuchs, B., Prat, O. P., Palecki, M., & Ansari, S. (2022). Characterizing U.S. drought over the past 20 years using the U.S. drought monitor. *International Journal of Climatology*, *42*(12), 6616–6630. https://doi.org/10.1002/joc.7653

Leng, G., & Hall, J. (2019). Crop yield sensitivity of global major agricultural countries to droughts and the projected changes in the future. *Science of The Total Environment*, *654*, 811–821. https://doi.org/10.1016/j.scitotenv.2018.10.434

Liu, M., Shamdasani, Y., & Taraz, V. (2023). Climate Change and Labor Reallocation: Evidence from Six Decades of the Indian Census. *American Economic Journal: Economic Policy*, *15*(2), 395–423. https://doi.org/10.1257/pol.20210129

Mertz, O., Halsnæs, K., Olesen, J. E., & Rasmussen, K. (2009). Adaptation to Climate Change in Developing Countries. *Environmental Management*, *43*(5), 743–752. https://doi.org/10.1007/s00267-008-9259-3

Mueller, V. A., & Osgood, D. E. (2009). Long-term Impacts of Droughts on Labour Markets in Developing Countries: Evidence from Brazil. *The Journal of Development Studies*, *45*(10), 1651–1662. https://doi.org/10.1080/00220380902935865

Nguyen, H., Thompson, A., & Costello, C. (2023). Impacts of historical droughts on maize and soybean production in the southeastern United States. *Agricultural Water Management, 281*, 108237. https://doi.org/10.1016/j.agwat.2023.108237

Strobl, E. (2011). The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties. *The Review of Economics and Statistics*, *93*(2), 575–589. https://doi.org/10.1162/REST_a_00082

Strobl, E. (2012). The economic growth impact of natural disasters in developing countries: Evidence from hurricane strikes in the Central American and Caribbean regions. *Journal of Development Economics*, *97*(1), 130–141. https://doi.org/10.1016/j.jdeveco.2010.12.002

Sutanto, S. J., Zarzoza Mora, S. B., Supit, I., & Wang, M. (2024). Compound and cascading droughts and heatwaves decrease maize yields by nearly half in Sinaloa, Mexico. *Npj Natural Hazards*, *1*(1), 1–8. https://doi.org/10.1038/s44304-024-00026-7

Swiss Re. (2024). *Sigma*. Swiss Re Institute. https://www.swissre.com/dam/jcr:73c636f8-1d47-4779-b757-845023332971/sigma-2-2024-life-annuity-insurance.pdf

Williams, P., Cook, E. R., Smerdon, J. E., Cook, B. I., Abatzoglou, J. T., Bolles, K., Baek, S. H., Badger, A. M., & Livneh, B. (2020). Large contribution from anthropogenic warming to an emerging North American megadrought. *Science*, *368*(6488), 314–318. https://doi.org/10.1126/science.aaz9600

Tables

Table 1: Effects on agricultural production and yields

	Volume (1)	Yield (2)
10-weeks of drought	-0.014**	-0.012***
	(0.007)	(0.002)
Observations	208,723	208,723
Municipalities	2,302	2,302
R-squared	0.963	0.986
Panel FE	X	X
Crop X Year FE	X	X
Irrigation X Year FE	X	X

Notes: This table reports the results from estimating the following model: $Y_{c,s,r,m,t} = \alpha + \beta X_{m,t} + \mu_{c,s,r,m} + \mu_{c,t} + \mu_{r,t} + \epsilon_{c,s,r,m,t}$, where the outcome variable is observed at the crop (c), cycle (s), irrigation type (r), municipality (m), and year (t) levels. The outcome variables include the logarith of production volume and yield obtained from the Statistical Yearbook of Agricultural Production from SIAP. The notation ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses.

Table 2: Effects on employment: total, agricultural, and non-agricultural

	All (1)	Non Agricultural (2)	Agricultural (3)
10-weeks of drought	-0.013** (0.006)	-0.006 (0.005)	-0.015** (0.007)
Observations	190,312	45,869	144,443
Municipalities	2,268	486	1,782
R-squared	0.983	0.993	0.973
Time FE	X	X	X
Month X Mun FE	X	X	X
Municipal linear trend	X	X	X

Notes: This table presents the results from estimating the following equation: $y_{m,t} = \alpha + \beta X_{m,t} + \mu_t + \mu_{year}\mu_m + \mu_{month}\mu_m + \epsilon_{m,t}$, where the outcome variable $y_{m,t}$ represents total employment in municipality (m) at month (t). We utilize public administrative data from IMSS which comprises information on formal employment data by sector, gender, and age in a monthly basis from April 2016 to February 2024. We report point estimates of the effect of ten weeks of exposure to extreme drought over a one-year window. Standard errors, shown in parentheses, are clustered at the municipal level. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

Table 3: Availability of financing tools by poverty

	Municipalities with positive values	Low	Medium low	Medium high	High
	(1)	(2)	(3)	(4)	(5)
Population (national)	2466	25.07	24.94	25.22	24.77
Revolving credit	2357	40.71	29.47	21.19	8.64
Non-revolving credit	2348	36.20	29.10	23.79	10.91
Low quality	2372	34.27	28.54	24.45	12.74
High quality	2366	37.52	29.48	23.34	9.66
Deposits	2453	52.05	30.31	13.93	3.70
Remittances	2443	20.39	25.70	31.51	22.40

Notes: Municipalities are grouped into quartiles based on their poverty share, using population-weighted thresholds. The table reports the distribution of financial tools, including credit (revolving and non-revolving by quality), deposits, and remittances, across these poverty groups at the first available period for each dataset.

Table 4: Credit conditions of financing tools by poverty

	Total (1)	**Low** (2)	**Medium low** (3)	**Medium high** (4)	**High** (5)
Revolving credit					
Number of credit card loans	25,800,046	9,765,731	7,414,142	5,966,662	2,646,511
Average interest rate (%)	51.86	48.51	49.43	50.62	53.25
Average credit amount (MXN)	7,923	12,842	10,627	9,141	6,311
Low quality non-revolving credit					
Number of credits	16,504,927	3,320,811	4,246,830	4,979,232	3,958,054
Average interest rate (%)	50.10	36.00	42.41	47.56	54.39
Average credit amount (MXN)	12,020	19,384	13,912	11,917	10,743
High quality non-revolving credit					
Number of credits	5,762,884	2,112,065	1,676,239	1,358,736	615,844
Average interest rate (%)	22.78	21.19	22.14	22.67	23.15
Average credit amount (MXN)	58,441	59,332	54,850	54,849	60,386

Notes: As in Table 3, municipalities are grouped into quartiles based on their poverty share, using population-weighted thresholds. This table presents credit conditions—measured by credit penetration (number of accounts), average interest rates, and average credit amounts—across poverty groups for both revolving and non-revolving credit products, distinguishing between low- and high-quality credit. We use revolving and non-revolving credit data for 2022, when more detailed data is available for credit card loans.

Table 5: Summary statistics

Variable	Total (1)	No agriculture (2)	Agriculture (3)	Difference (4)
Credit card loans				
Non-performing credit (MDP)	0.120	0.321	0.024	-0.297***
	(0.776)	(1.336)	(0.101)	(0.001)
Performing credit (MDP)	2.858	7.963	0.423	-7.539***
	(18.913)	(32.570)	(2.019)	(0.019)
Total outstanding credit (MDP)	2.977	8.283	0.447	-7.836***
	(19.500)	(33.572)	(2.081)	(0.020)
Number of credit card loans	228.524	585.713	58.205	-527.509***
	(1,173)	(1,999)	(197.486)	(1.193)
Delinquency rate (%)	6.104	5.634	6.328	0.694***
	(15.031)	(11.803)	(16.342)	(0.016)
Distance to credit limit (MXN)	26,188	30,203	24,338	-5,865***
	(683,676)	(476,409)	(760,408)	(752.351)
Credit limit (MXN)	38,974	49,120	34,298	-14,821***
	(857,940)	(1,034,000)	(763,221)	(944.097)
Interest rate (%)	55.887	54.359	56.591	2.232***
	(14.143)	(12.851)	(14.646)	(0.016)
Low-quality non-revolving credit				
Non-performing credit (MDP)	0.124	0.291	0.035	-0.256***
	(0.641)	(1.050)	(0.135)	(0.001)
Performing credit (MDP)	1.968	4.488	0.622	-3.866***
	(9.856)	(16.114)	(2.262)	(0.010)
Total outstanding credit (MDP)	2.092	4.778	0.656	-4.122***
	(10.306)	(16.843)	(2.343)	(0.011)
Number of credits	197.705	399.225	90.053	-309.172***
	(1,165)	(1,889)	(380.510)	(1.237)
Delinquency rate (%)	6.454	6.436	6.463	0.027
	(15.507)	(13.387)	(16.529)	(0.017)
High-quality non-revolving credit				
Non-performing credit (MDP)	0.100	0.238	0.022	-0.216***
	(0.616)	(0.963)	(0.228)	(0.001)
Performing credit (MDP)	4.135	9.773	0.940	-8.833***
	(20.886)	(32.669)	(7.094)	(0.024)
Total outstanding credit (MDP)	4.236	10.011	0.962	-9.049***
	(21.417)	(33.496)	(7.287)	(0.024)
Number of credits	75.386	174.863	19.001	-155.862***
	(363.550)	(583.472)	(73.008)	(0.412)
Delinquency rate (%)	2.555	2.867	2.378	-0.489***
	(10.526)	(9.894)	(10.865)	(0.012)
Other financing tools				
Annual remittances per capita	3,755	3,140	4,039	899.000***
	(5,723)	(4,999)	(6,006)	(8.262)
Deposits per capita	1,215	1,628	824	-803.427***
	(4,932)	(6,738)	(2,022)	(13.757)
Socioeconomic characteristics				
Share of population below the poverty line	0.597	0.431	0.678	0.248***
	(0.197)	(0.150)	(0.164)	(0.000)
Share of population in the formal sector	0.360	0.334	0.373	0.039***
	(0.148)	(0.110)	(0.161)	(0.000)
Share of illiterate population	0.299	0.215	0.340	0.126***
	(0.099)	(0.063)	(0.087)	(0.000)
Share of agriculture workers	0.241	0.042	0.337	0.295***
	(0.192)	(0.034)	(0.160)	(0.000)
Droughts				
Annual weeks of moderate drought	2.566	2.356	2.666	0.310***
	(1.340)	(1.359)	(1.320)	(0.001)
Annual weeks of extreme drought	0.134	0.105	0.148	0.042***
	(0.458)	(0.418)	(0.475)	(0.000)

Notes: Authors' estimates are based on cell-level data from Banco de México proprietary datasets on revolving and non-revolving consumer credit, from April 2016 to February 2024. The table also includes publicly available datasets on bank deposits from the CNBV and remittance flows from Banco de México. Socioeconomic characteristics are drawn from the 2020 Population and Housing Census and CONEVAL, while drought indicators are obtained from CONAGUA's Drought Monitor. The table shows the descriptive statistics for the full sample, non-agricultural and agricultural municipalities as well as their statistical differences. We classify municipalities as agricultural if more than the 11.3% (national average) of the labor force works in the agricultural sector, and as non-agricultural otherwise. The notation ***, **, and * correspond to statistical significance levels of 1%, 5%, and 10%, respectively. Standard errors in parenthesis.

Table 6: Effects on credit card loans' delinquency rate

	(1)	(2)	(3)	(4)	(5)
10-weeks of drought	0.123***	0.095***	0.082***	0.082***	0.107***
	(0.028)	(0.025)	(0.026)	(0.026)	(0.038)
Observations	4,227,061	4,227,061	4,227,061	4,227,061	4,227,061
Municipalities	2,460	2,460	2,460	2,460	2,460
R-squared	0.017	0.164	0.279	0.281	0.294
Time FE	X	X	X	X	X
Municipality FE	X	X	X	X	X
Bank FE	-	X	X	X	X
Cell FE	-	-	X	X	X
Bank X Time FE	-	X	X	X	X
Month X Mun FE	-	-	-	X	X
Year X Mun FE	-	-	-	-	X

Notes: This table presents results from estimating Equation 1 with the delinquency rate as the dependent variable. The analysis uses cell-level data from the Banco de México proprietary credit card loans' dataset covering the period from April 2016 to February 2024. The cells reflect the maximum level of granularity available in our data, which corresponds to the municipality-by-gender-by-age-by-bank level. It reports point estimates of the effect of ten weeks of exposure to extreme drought conditions over a one-year window. Standard errors, shown in parentheses, are clustered at the municipal level. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

Table 7: Effects on credit card loans' intensive and extensive margins

	Delinquency Rate (1)	Non Performing Loans (2)	Performing Loans (3)	Total Outstanding Credit (4)	Number of Credit Card Loans (5)
Panel A: All					
10-weeks of drought	0.107***	0.029***	0.000	0.003	-0.001**
	(0.038)	(0.010)	(0.003)	(0.002)	(0.001)
Observations	4,227,061	4,227,061	4,227,061	4,227,061	4,227,061
Municipalities	2,460	2,460	2,460	2,460	2,460
R-squared	0.294	0.668	0.834	0.890	0.976
Panel B: No agricultural municipalities					
10-weeks of drought	0.037	0.011	0.007	0.006*	-0.002
	(0.052)	(0.019)	(0.004)	(0.003)	(0.001)
Observations	1,364,980	1,364,980	1,364,980	1,364,980	1,364,980
Municipalities	502	502	502	502	502
R-squared	0.342	0.730	0.909	0.935	0.984
Panel C: Agricultural municipalities					
10-weeks of drought	0.128***	0.041***	0.000	0.003	-0.001
	(0.048)	(0.012)	(0.004)	(0.003)	(0.001)
Observations	2,862,062	2,862,062	2,862,062	2,862,062	2,862,062
Municipalities	1,958	1,958	1,958	1,958	1,958
R-squared	0.283	0.585	0.752	0.831	0.963
Time FE	X	X	X	X	X
Cell FE	X	X	X	X	X
Bank X Time FE	X	X	X	X	X
Month X Mun FE	X	X	X	X	X
Year X Mun FE	X	X	X	X	X

Notes: This table presents results from estimating Equation 1 with the delinquency rate, non-perfoming loans, performing loans, total outstanding credit, and number of credit card loans' as dependent variables for the full sample, and the division into agricultural and non-agricultural municipalities. The analysis uses cell-level data from the Banco de México proprietary credit card loans' dataset covering the period from April 2016 to February 2024. It reports point estimates of the effect of ten weeks of exposure to extreme drought conditions over a one-year window. Standard errors, shown in parentheses, are clustered at the municipal level. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

Table 8: Effects on credit card loans by socioeconomic characteristics

	Low			High		
	Delinquency Rate	Non Performing Loans	Performing Loans	Delinquency Rate	Non Performing Loans	Performing Loans
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Labor Informality						
10-weeks of drought	0.085	0.031*	-0.001	0.153**	0.048***	0.002
	(0.071)	(0.019)	(0.005)	(0.064)	(0.016)	(0.005)
Observations	1,355,730	1,355,730	1,355,730	1,499,852	1,499,852	1,499,852
R-squared	0.284	0.584	0.755	0.284	0.590	0.762
Panel B: Illiteracy						
10-weeks of drought	0.066	0.026*	0.001	0.243**	0.066***	-0.000
	(0.052)	(0.015)	(0.004)	(0.099)	(0.023)	(0.008)
Observations	1,837,401	1,837,401	1,837,401	1,018,183	1,018,183	1,018,183
R-squared	0.281	0.603	0.785	0.286	0.536	0.686
Panel C: Poverty						
10-weeks of drought	0.037	0.019	-0.003	0.328***	0.082***	0.013
	(0.052)	(0.015)	(0.004)	(0.104)	(0.022)	(0.009)
Observations	1,882,271	1,882,271	1,882,271	973,311	973,311	973,311
R-squared	0.278	0.603	0.787	0.288	0.535	0.670
Time FE	X	X	X	X	X	X
Cell FE	X	X	X	X	X	X
Bank X Time FE	X	X	X	X	X	X
Month X Mun FE	X	X	X	X	X	X
Year X Mun FE	X	X	X	X	X	X

Notes: This table presents results from estimating Equation 1, using the delinquency rate and its components as dependent variables for agricultural municipalities. The sample is further divided based on median values of several socioeconomic dimensions—such as labor informality, illiteracy, and poverty—to explore heterogeneous effects. The analysis uses cell-level data from the Banco de México proprietary credit card loans' dataset covering the period from April 2016 to February 2024. It reports point estimates of the effect of ten weeks of exposure to extreme drought conditions over a one-year window. Standard errors, shown in parentheses, are clustered at the municipal level. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

Table 9: Effects on credit card loans by credit characteristics

	Low			**High**		
	Delinquency Rate	Non Performing Loans	Performing Loans	Delinquency Rate	Non Performing Loans	Performing Loans
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Interest rate						
10-weeks of drought	0.022	0.028	0.001	0.221***	0.041**	0.003
	(0.047)	(0.017)	(0.004)	(0.079)	(0.018)	(0.006)
Observations	1,309,584	1,309,584	1,309,584	1,304,458	1,304,458	1,304,458
R-squared	0.258	0.598	0.820	0.297	0.595	0.696
Panel B: Credit limit						
10-weeks of drought	0.247***	0.046**	0.002	0.018	0.022	0.005
	(0.085)	(0.018)	(0.006)	(0.048)	(0.017)	(0.004)
Observations	1,237,147	1,237,147	1,237,147	1,376,911	1,376,911	1,376,911
R-squared	0.306	0.650	0.729	0.138	0.532	0.790
Panel C: Absolute distance to credit card limit						
10-weeks of drought	0.254***	0.036**	-0.001	0.010	0.027	0.003
	(0.087)	(0.018)	(0.006)	(0.048)	(0.017)	(0.004)
Observations	1,238,709	1,238,709	1,238,709	1,375,375	1,375,375	1,375,375
R-squared	0.308	0.653	0.724	0.138	0.528	0.800
Time FE	X	X	X	X	X	X
Cell FE	X	X	X	X	X	X
Bank X Time FE	X	X	X	X	X	X
Month X Mun FE	X	X	X	X	X	X
Year X Mun FE	X	X	X	X	X	X

Notes: This table presents results from estimating Equation 1, using the delinquency rate and its components as dependent variables for agricultural municipalities. The sample is further divided based on median values of several credit characteristics in 2022—such as interest rate, credit limit, and absolute distance to credit limit—to explore heterogeneous effects. The analysis uses cell-level data from the Banco de México proprietary credit card loans' dataset covering the period from April 2016 to February 2024. It reports point estimates of the effect of ten weeks of exposure to extreme drought conditions over a one-year window. Standard errors, shown in parentheses, are clustered at the municipal level. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

Table 10: Effects on non-revolving credit intensive and extensive margins

	Delinquency Rate (1)	Non Performing Loans (2)	Performing Loans (3)	Total Outstanding Credit (4)	Number of Credit Card Loans (5)
Panel A: All					
10-weeks of drought	-0.014	0.012	0.004	0.003	0.001
	(0.038)	(0.015)	(0.005)	(0.003)	(0.002)
Observations	592,102	592,102	592,102	592,102	592,102
Municipalities	1,909	1,909	1,909	1,909	1,909
R-squared	0.345	0.626	0.769	0.880	0.959
Panel B: Low Quality					
10-weeks of drought	0.017	0.025	0.005	0.004	-0.000
	(0.057)	(0.019)	(0.007)	(0.004)	(0.003)
Observations	415,982	415,982	415,982	415,982	415,982
Municipalities	1,906	1,906	1,906	1,906	1,906
R-squared	0.348	0.615	0.710	0.863	0.956
Panel C: High Quality					
10-weeks of drought	-0.050	0.026	0.016***	0.013***	0.004*
	(0.037)	(0.016)	(0.006)	(0.004)	(0.002)
Observations	346,494	346,504	346,504	346,504	346,504
Municipalities	1,893	1,893	1,893	1,893	1,893
R-squared	0.339	0.524	0.825	0.894	0.943
Time FE	X	X	X	X	X
Cell FE	X	X	X	X	X
Bank X Time FE	X	X	X	X	X
Month X Mun FE	X	X	X	X	X

Notes: This table presents results from estimating Equation 1 with the delinquency rate and its components as the dependent variable for the last bimester of each year. The analysis uses cell-level data from the Banco de México proprietary consumption non-revolving credits dataset from December 2016 to December 2023. It reports point estimates of the effect of ten weeks of exposure to extreme drought conditions over a one-year window. Standard errors, shown in parentheses, are clustered at the municipal level. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

Table 11: Effects on deposits by municipality type, and on credit card loans' delinquency rates by deposits per capita

	Effects on deposits		**Effects on delinquency rates**	
	Non-agricultural	Agricultural	Low deposits per capita	High deposits per capita
	(1)	(2)	(3)	(4)
10-weeks of drought	0.009	-0.038***	0.252*	0.085*
	(0.006)	(0.010)	(0.134)	(0.051)
Observations	300,859	342,234	861,475	1,999,866
Municipalities	501	1,948	976	977
R-squared	0.948	0.972	0.278	0.286
Time FE	X	X	X	X
Cell FE	X	X	X	X
Bank X Time FE	X	X	X	X
Month X Mun FE	X	X	X	X
Year X Mun FE	X	X	X	X

Notes: Columns 1 and 2 show the effects on monthly bank deposits at the municipal level, using publicly available date from CNBV. The model specification in these columns is $log(y_{b,m,t}) = \alpha + \beta X_{m,t} + \mu_{b,m} + \mu_t + \mu_{b,t} + \mu_{year} \times \mu_m + \mu_{month} \times \mu_m + \epsilon_{b,m,t}$, which is estimated separately by levels of agricultural employment from April 2016 to February 2024. Due to differences in data granularity, the cells used in the deposit and credit specifications differ and reflect the maximum level of detail available in each dataset. For deposits, the analysis is conducted at the bank-by-municipality level, while for credit, we use the standard cell structure defined by bank-by-municipality-by-gender-by-age group. Columns 3 and 4 present results from estimating Equation 1 with the delinquency rate as the dependent variable for agricultural municipalities. The sample is divided based on median values of deposits per capita to examine potential heterogeneous effects. The analysis uses cell-level data from Banco de México proprietary credit card loans' dataset from April 2016 to February 2024. It reports point estimates of the effect of ten weeks of exposure to extreme drought conditions over a one-year window. Standard errors, shown in parentheses, are clustered at the municipal level. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

Table 12: Effects on remittances by municipality type, and on credit card loans' delinquency rates by remittances per capita

	Effects on remittances		**Effects on delinquency rates**	
	Non-agricultural	Agricultural	Low remittances per capita	High remittances per capita
	(1)	(2)	(3)	(4)
10-weeks of drought	0.055**	0.163***	0.297***	0.057
	(0.026)	(0.027)	(0.107)	(0.053)
Observations	16,467	64,152	1,010,616	1,830,703
Municipalities	499	1,944	970	972
R-squared	0.937	0.905	0.281	0.283
Time FE	X	X	X	X
Municipality FE	X	X	X	X
Cell FE	-	-	X	X
Bank X Time FE	-	-	X	X
Year X Mun FE	-	-	X	X
Month X Mun FE	X	X	X	X
Municipal linear trend	X	X	-	-

Notes: Columns 1 and 2 show the effects on the cumulative remittances per capita received over the past 12 months. As remittances data from Banco de México are reported quarterly, drought data are aligned with the last month of each quarter. The estimated model is $y_{m,t} = \alpha + \beta X_{m,t} + \mu_m + \mu_t + \mu_{year} \times \mu_m + \mu_{month} \times \mu_m + \epsilon_{m,t}$, which is estimated separately by levels of agricultural employment from March 2016 to March 2024. While the specification is not exactly the same as in Equation 1, due to differences in data granularity, the cells used in the deposit and credit specifications differ and reflect the maximum level of detail available in each dataset. For remittances, the analysis is conducted at the municipality level, while for credit, we use the standard cell structure defined by bank-by-municipality-by-gender-by-age group. Columns 3 and 4 present results from estimating Equation 1 with the delinquency rate as the dependent variable for agricultural municipalities. The sample is divided based on median values of remittances per capita to examine potential heterogeneous effects. The analysis uses cell-level data from Banco de México proprietary credit card loans' dataset from January 2016 to March 2024. It reports point estimates of the effect of ten weeks of exposure to extreme drought conditions over a one-year window. Standard errors, shown in parentheses, are clustered at the municipal level. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

Table 13: Seasonal behavior of credit card loans

	Bimester					
	(2)	(4)	(6)	(8)	(10)	(12)
Panel A: Delinquency Rate						
10-weeks of drought	0.096**	0.222***	0.060	0.034	0.122**	0.039
	(0.043)	(0.073)	(0.062)	(0.051)	(0.052)	(0.049)
R-squared	0.361	0.383	0.366	0.355	0.357	0.331
Panel B: Non-Performing Loans						
10-weeks of drought	0.067***	0.103***	0.055***	0.036**	0.068***	0.055***
	(0.013)	(0.020)	(0.019)	(0.016)	(0.016)	(0.015)
R-squared	0.621	0.627	0.622	0.623	0.629	0.618
Panel C: Performing Loans						
10-weeks of drought	0.005	0.005	0.002	0.006	0.011**	0.013***
	(0.004)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
R-squared	0.781	0.782	0.780	0.782	0.780	0.785
Panel D: Total Outstanding Credit						
10-weeks of drought	0.008**	0.006	0.000	0.003	0.012**	0.015***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)
R-squared	0.824	0.828	0.824	0.823	0.821	0.824
Panel E: Number of Credit Card Loans						
10-weeks of drought	0.004**	0.003	0.001	-0.002	0.002	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R-squared	0.960	0.960	0.961	0.960	0.961	0.961
Observations	498,291	451,329	464,864	464,748	462,025	467,372
Time FE	X	X	X	X	X	X
Cell FE	X	X	X	X	X	X
Time x Bank FE	X	X	X	X	X	X
Month x Mun FE	X	X	X	X	X	X

Notes: This table presents results from estimating Equation 1 by bimester for the delinquency rate, non-perfoming loans, performing loans, total outstanding credit, and number of credit card loans as dependent variables. The analysis uses cell-level data from Banco de México proprietary credit card loans' dataset from April 2016 to February 2024. It reports point estimates of the effect of ten weeks of exposure to extreme drought conditions over a one-year window. Standard errors, shown in parentheses, are clustered at the municipal level. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

Table 14: Seasonal behavior of non-revolving credit

	Bimester					
	(2)	(4)	(6)	(8)	(10)	(12)
Panel A: Non Performing Loans						
10-weeks of drought	0.010	0.013	0.036**	0.002	-0.013	0.012
	(0.013)	(0.019)	(0.017)	(0.017)	(0.016)	(0.015)
R-squared	0.632	0.640	0.624	0.626	0.630	0.626
Panel B: Performing Loans						
10-weeks of drought	0.010**	-0.000	-0.004	-0.001	0.003	0.004
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
R-squared	0.770	0.786	0.766	0.771	0.773	0.769
Panel C: Non Performing Low Quality Loans						
10-weeks of drought	0.031*	0.038*	0.063***	0.046**	0.018	0.025
	(0.018)	(0.022)	(0.020)	(0.020)	(0.019)	(0.019)
R-squared	0.626	0.636	0.617	0.619	0.622	0.615
Panel D: Performing Low Quality Loans						
10-weeks of drought	0.017**	-0.000	0.008	0.000	-0.002	0.005
	(0.006)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
R-squared	0.714	0.731	0.710	0.716	0.717	0.710
Panel E: Non Performing High Quality Loans						
10-weeks of drought	0.003	-0.011	0.004	-0.022	-0.004	0.026
	(0.014)	(0.021)	(0.018)	(0.018)	(0.017)	(0.016)
R-squared	0.522	0.531	0.521	0.519	0.524	0.524
Panel F: Performing High Quality Loans						
10-weeks of drought	0.017***	-0.003	-0.001	0.008	0.019***	0.016***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
R-squared	0.827	0.811	0.826	0.824	0.827	0.825
Time FE	X	X	X	X	X	X
Cell FE	X	X	X	X	X	X
Bank X Time FE	X	X	X	X	X	X
Month X Mun FE	X	X	X	X	X	X

Notes: This table reports the results of estimating Equation 1 separately for each bimester, using non-performing and performing loans as dependent variables. We present point estimates for non-revolving credit, both in aggregate and disaggregated by credit quality. The analysis uses cell-level data from Banco de México proprietary consumption loans datasets from April 2016 to February 2024. It reports point estimates of the effect of ten weeks of exposure to extreme drought conditions over a one-year window. Standard errors, shown in parentheses, are clustered at the municipal level. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

Table 15: Effects on performing credit card loans by credit conditions

	Interest Rate		**Credit limit**		**Distance**	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
10-weeks of drought	-0.003	0.030***	0.021***	0.009	0.021***	0.006
	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)
Observations	214,456	221,329	208,337	227,452	208,403	227,387
Municipalities	1,907	1,951	1,949	1,894	1,950	1,898
R-squared	0.827	0.710	0.746	0.795	0.742	0.803
Time FE	X	X	X	X	X	X
Cell FE	X	X	X	X	X	X
Bank X Time FE	X	X	X	X	X	X
Month X Mun FE	X	X	X	X	X	X

Notes: This table presents results from estimating Equation 1 in the last bimester of each year using performing loans as dependent variable for agricultural municipalities. The sample is further divided based on median values of several credit characteristics in 2022—such as interest rate, credit limit, and absolute distance to credit limit—to explore heterogeneous effects. The analysis uses cell-level data from Banco de México proprietary credit card loans' dataset from April 2016 to February 2024. It reports point estimates of the effect of ten weeks of exposure to extreme drought conditions over a one-year window. Standard errors, shown in parentheses, are clustered at the municipal level. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

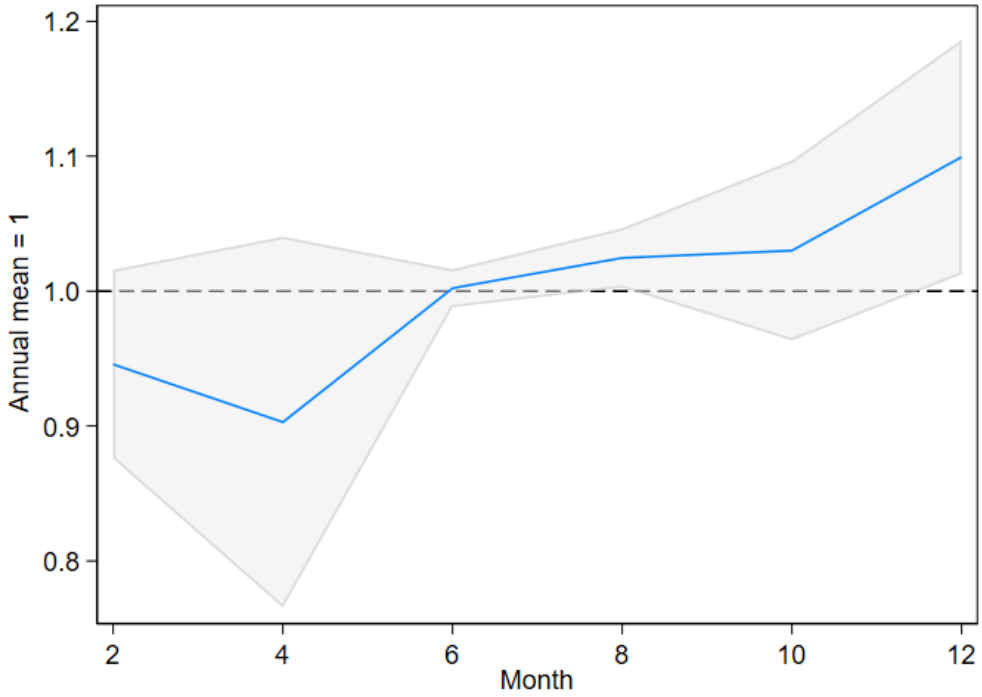
Table 16: Effects on deposits and remittances by credit conditions

	Interest rate		**Credit limit**		**Distance**	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Remittances						
10-weeks of drought	0.178***	0.256***	0.058	0.220***	0.098	0.140***
	(0.045)	(0.067)	(0.069)	(0.043)	(0.071)	(0.041)
Observations	7,800	7,720	7,760	7,760	7,768	7,752
Municipalities	975	965	970	970	971	969
R-squared	0.915	0.888	0.886	0.912	0.882	0.916
Time FE	X	X	X	X	X	X
Month X Mun FE	X	X	X	X	X	X
Municipal linear trend	X	X	X	X	X	X
Panel B: Deposits						
10-weeks of drought	-0.053***	-0.003	-0.013	-0.050***	-0.007	-0.047***
	(0.017)	(0.021)	(0.024)	(0.016)	(0.028)	(0.016)
Observations	17,081	10,206	9,437	17,858	8,156	19,136
Municipalities	973	968	969	972	969	972
R-squared	0.959	0.954	0.949	0.958	0.934	0.954
Time FE	X	X	X	X	X	X
Cell FE	X	X	X	X	X	X
Bank X Time FE	X	X	X	X	X	X
Month X Mun FE	X	X	X	X	X	X

Notes: Panel A reports for the cumulative remittances per capita received over the past 12 months as the outcome variable. As remittances data from Banco de México are reported quarterly, drought data are aligned with the last month of each quarter. The estimated model is $log(y_{m,t}) = \alpha + \beta X_{m,t} + \mu_m + \mu_t + \mu_{year} \times \mu_m + \mu_{month} \times \mu_m + \epsilon_{m,t}$. In Panel B, the model specification in these columns is $log(y_{b,m,t}) = \alpha + \beta X_{m,t} + \mu_{b,m} + \mu_t + \mu_{b,t} + \mu_{year} \times \mu_m + \mu_{month} \times \mu_m + \epsilon_{b,m,t}$ using deposits as the outcome variable. Deposits specification the cell represents the maximum granurality of our data, which is municipality-by-bank. This is estimated separately by levels of agricultural employment from April 2016 to February 2024. Both models are estimated separately dividing the sample based on median values of several credit characteristics in 2022—such as interest rate, credit limit and absolute distance to credit limit at municipality level to explore heterogeneous effects.

Figures

Figure 1: Seasonal behavior of credit card loans' performing credit



Notes: This figure shows the ratio of the average monthly credit card loans' balances to the annual mean, which allows us to see the seasonal pattern in credit card usage. We use cell-level data from Banco de México proprietary credit card loans' dataset, from April 2016 to October 2024. The shaded region represents a 95% confidence interval around the mean seasonal pattern.

Appendix A

Table A.1: Coping Mechanisms When Unable to Cover Expenses (ENIF)

The last time you were unable to cover your expenses	**All respondents** (1)	**With credit card** (2)	**With low-quality credit** (3)	**With high-quality credit** (4)	**Receiving remittances** (5)
Did you borrow money from family members or acquaintances?	51%	52%	61%	51%	58%
Did you use your savings?	42%	48%	53%	55%	46%
Did you request a salary advance, work extra hours, or take on temporary work?	17%	21%	23%	21%	18%
Did you use your credit card or apply for a loan from a bank or financial institution?	11%	31%	39%	15%	17%
Did you fall behind on the payment of any loan or credit?	9%	16%	20%	11%	14%
Did you reduce your spending?	69%	73%	74%	73%	73%

Notes: Estimates are derived from the 2024 National Survey on Financial Inclusion (ENIF), conducted by INEGI and CNBV. Reported percentages correspond to response frequencies computed over the relevant respondent base. The survey design ensures representativeness at both national and subnational levels.

Table A.2: Credit distribution, extensive margin

	Municipalities with positive values	Low	Medium low	Medium high	High
	(1)	(2)	(3)	(4)	(5)
Population (national)	2466	25.07	24.94	25.22	24.77
Revolving credit	2357	34.43	28.07	22.71	14.79
Non-revolving credit	2348	26.46	26.31	27.53	19.69
Low quality	2372	23.20	25.26	28.79	22.76
High quality	2366	36.32	29.51	23.74	10.43
Deposits	2453	52.05	30.31	13.93	3.70
Remittances	2443	20.39	25.70	31.51	22.40

Notes: Municipalities are grouped into quartiles based on their poverty share, using population-weighted thresholds. The table reports the distribution of financing tools, including the number of credits (revolving and non-revolving by quality), deposits, and remittances, across these poverty groups at the first available period for each dataset.

Table A.3: Horse-race between moderate and extreme droughts

	Delinquency Rate (1)	Non Performing Loans (2)	Performing Loans (3)	Total Outstanding Credit (4)	Number of Credit Card Loans (5)
Exceptional drought (10-weeks)	0.159***	0.042***	-0.001	0.001	0.000
	(0.052)	(0.013)	(0.004)	(0.003)	(0.001)
Moderate drought (10-weeks)	0.042*	0.003	-0.001	-0.002	0.001
	(0.024)	(0.006)	(0.002)	(0.001)	(0.000)
Observations	2,857,356	2,857,356	2,857,356	2,857,356	2,857,356
R-squared	0.283	0.587	0.759	0.811	0.963
Time FE	X	X	X	X	X
Cell FE	X	X	X	X	X
Bank X Time FE	X	X	X	X	X
Month X Mun FE	X	X	X	X	X
Year X Mun FE	X	X	X	X	X

Notes: This table presents results from estimating Equation 1 with the delinquency rate, non-performing loans, performing loans, total outstanding credit, and number of cards as dependent variables. The analysis uses cell-level data from Banco de México proprietary credit card loans' dataset from April 2016 to February 2024. It reports point estimates of the effect of ten weeks of exposure to extreme drought conditions over a one-year window. Standard errors, shown in parentheses, are clustered at the municipal level. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

Table A.4: Relationship between credit conditions, poverty, remittances, and deposits

	Poverty		Remittances		Deposits	
	Low	High	Low	High	Low	High
Interest rate						
Low	64.72	35.28	39.59	60.41	37.93	62.07
High	35.46	64.54	60.31	39.69	62.04	37.96
Credit limit						
Low	31.28	68.72	64.43	35.57	65.91	34.09
High	68.95	31.05	35.36	64.64	34.02	65.98
Distance						
Low	28.10	71.90	68.90	31.10	72.48	27.52
High	72.13	27.87	30.86	69.14	27.46	72.54

Notes: This table presents municipal groups based on median values of selected credit characteristics (interest rate, credit limit, and absolute distance to the credit limit) measured in 2022, as well as socioeconomic dimensions (poverty from the 2020 Population and Housing Census) and financing characteristics (remittances per capita from January 2016 to March 2024, and deposits per capita from April 2016 to February 2024). Each cell reports the share (percentage) of municipalities classified within each combination of groups.