DO WEATHER SHOCKS AFFECT BANKS' LOAN PORTFOLIO? EVIDENCE FROM COLOMBIA

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Do weather shocks affect banks' loan portfolio? Evidence from Colombia*

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Abstract

The materialization of climate-related risks has become a relevant issue since it is directly affecting the economic sectors. The Colombian banking sector is no exception, as it is exposed to climate-related financial risks. By combining information on bank portfolio and loan provisions by municipality, with quarterly rainfall records from more than 2,000 weather stations located across the country, I examine the relationship between climate variability (rainfall and rain shocks) and credit dynamics by type of loans. I find that during episodes of heavy rainfall the consumer and microcredit portfolio, as well as the consumer loan provisions, increase. On the contrary, heavy rainfall shocks have a negative impact on housing portfolio and housing loan provisions. These results illustrate that, during an episode of heavy rainfall, individuals could face a negative income shock. To cope with this, households resort to consumer loans, and small and medium enterprises resort to microcredit loans. Furthermore, since buying a house may not be a priority as it is to satisfy basic needs, housing loans decrease. Finally, I also examine whether the effect of the rainfall shocks on the commercial loan portfolio varies with banks exposure to different economic sectors. I find a positive effect of episodes of heavy rainfall on commercial loans for banks with high loan concentrations in the agricultural, services, and health sectors.

Keywords: Colombia, bank lending, weather shocks
JEL Classification: R23, G21, Q54

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1 Introduction

During the last few years climate change has gained worldwide relevance given the increasing frequency and intensity of adverse natural events. There is consensus that consequences of risks related to climate change spread out over the economic system. As for the financial system, climate change risks could be elevated for banks through the microeconomic transmission channels. In this regard, Basel Committee on Banking Supervision (2021) summarizes each of the three climate risk drivers that can affect banks: i) through its counterparties (households, corporates and sovereigns), banks' credit risk may increase; ii) through the value of financial assets, market risk may increase; and iii) through deposits and funding costs, liquidity risk may increase.

The credit channel is a relevant propagation mechanism given that physical damages caused by natural events could affect the borrower's ability to meet its financial obligations, which could force banks to fire sale assets and to ration credit. Moreover, if the value of any pledged collateral or recoverable value decreases, banks would not be able to recover the value of a loan in an event of default. In that sense, risks related to climate change represent an income shock to banks. Similarly, borrowers could also face an income shock, but they could respond to this by either borrowing credit or failing to fulfil a financial obligation.

The Colombian banking sector is potentially exposed to climate-related financial risks, particularly physical risks, which include gradual changes in rainfall, rising sea levels and increasing temperatures. According to World Bank (2021), large scale riverine floods are the main climate-related disaster risk in Colombia. In fact, during 2010-2011, Colombia experienced a La Niña event, leading to several floods that caused losses of around US$7.0 billion (2.0 percent of the 2011 gross domestic product)[1].

On the contrary, during 2015-2016, Colombia experienced an El Niño event leading to a severe dry season that left the Magdalena River, the main river across the country, at its lowest historical levels. Consequently, more than half of the municipalities faced water scarcity and fires. However, losses were estimated to be lower than those recorded during 2010-2011 (0.7 percent of the 2015 gross domestic product)[2]. According to the Institute of Hydrology, Meteorology and Environmental Studies (IDEAM in Spanish), due to climate change, a decrease between 10 to 30% in the average rainfall can be expected in about 27% of the national territory, and an increase between 10 and 30% can be expected in about 14% of the national territory (IDEAM, 2015). The reductions in rainfall could lead to losses of water sources, and agricultural and forestry production, and the increase in rainfall could lead to landslides, as well as floods. Although floods can occur throughout the country, historically the highest levels are observed in the departments of Sucre, Bolívar, Antioquia, and Magdalena. Moreover, approximately 6.5% of banks' total loan exposures are in municipalities where more than 10% of the land area flooded during flood events (World Bank, 2021).

[1] In Cepal et al. (2013) authors determine the economic magnitude of the damage (destruction of assets) and the losses (alteration of flows) caused by the 2010-2011 winter wave in Colombia.

[2] In Melo et al. (2017) authors calculate the economic costs of the El Niño event in Colombia during 2015-2016

This paper analyses the effect of rainfall shocks, whose frequency may increase as a result of climate change, on banks' portfolio and loan provisions. Specifically, using a panel of Colombian banks, I investigate the extent to which increases in rainfall and transitory rainfall shocks lead banks to modify their loan provisions and loan portfolio. Rainfall is measured as the logarithm of quarterly rainfall measured in millimeters for each municipality, and rainfall shocks are defined following Bohorquez-Penuela et al. (2020) methodology, in which a positive shock (heavy rainfall) is observed when quarterly amount of rainfall is at or above the 80th percentile of the quarterly historical distribution for each municipality. Likewise, a negative shock (low rainfall) occurs when quarterly rainfall is at or below the 20th percentile. I estimate the historical distributions of rainfall by quarters and municipality to account for seasonality.

I use data from the Financial Superintendence of Colombia (SFC in Spanish) containing information on banks' portfolio and loan provisions by municipality, and a data set from the IDEAM of daily rainfall for more than 2,000 weather stations located across the country. I first examine the relationship between weather variability (rainfall and rainfall shocks) and credit dynamics by type of loans. Secondly, considering the differences of vulnerability of the economic sectors to changes in rainfall patterns, I aim to determine if there are heterogeneous effects depending on banks' exposure to vulnerable sectors. This is performed by identifying those banks whose share of economic sectors[3] to commercial loan portfolio is equal to or greater than the observed average share of all banks before 2010, the year in which more than half of the municipalities included in the sample faced heavy rainfall episodes. The average measure is chosen over the median measure since, in this way, it is possible to identify the banks whose commercial portfolio is highly exposed to the economic sectors analyzed. When the median share is chosen, in some sectors (specifically those whose total share to the commercial portfolio is low) many banks are identified as exposed, even though at an individual level those banks are not actually exposed. However, for robustness check, I also use the median share of all banks before 2010 to identify banks with high exposure to each economic sector.

I find a positive effect of excess of rainfall episodes on consumer and microcredit loans, and a negative impact on housing loans. These results coincide with the increase in demand for credit during 2010-2011, period in which more than half of the municipalities included in the sample faced heavy rainfall episodes. According to Fernández-Moreno et al. (2011), the demand for credit perceived by financial intermediaries increased during 2010-2011, except the demand for housing loans. In line with this, Del Ninno et al. (2003) point out that, after the 1998 flooding in Bangladesh, households with different levels of wealth increased their demand for credit to cope with higher food prices and lower incomes from employment disruptions. In this regard, during an episode of heavy rainfall, individuals could face a negative income shock (Bayudan-Dacuycuy and Baje, 2019; Bohorquez-Penuela et al., 2020), thus to cope with

[3] The economic sectors included in the analysis are: agriculture, manufacturing, construction, real estate, trade, transportation, electricity, restaurants and hotels, mining, services, and financial.

it, households resort to consumer loans, and small and medium enterprises (small businesses) resort to microcredit loans.

Furthermore, I find that heavy rainfall shocks increase consumer loan provisions and decrease housing loan provisions. This is explained by the counterparty risk, which refers to the risk of borrowers failing to meet their financial obligations. The increase in consumer loan provisions suggests that the banks are probably lending money to risky borrowers. Meanwhile, the housing loan provisions decrease as the housing portfolio shrinks, since banks are not lending to borrowers with different risk profiles. In this regard, Collier et al. (2011) argue that excess rainfall significantly increases problem loans (when loans cannot be repaid according to the terms of the initial agreement, banks will recognize these debt obligations as problem loans), specifically the level of restructured loans.

Regarding heterogeneous effects, I find a positive effect of excess of rainfall episodes on commercial loans for banks with high loan concentrations in the agricultural, services and health. As for the agricultural sector, this has to do with the fact that this sector was the most affected by the floods in 2010 and 2011 (37% of total damages). Moreover, Bohorquez-Penuela (2021) find that a La Niña event in Colombia is associated with an increase on the number of credits granted.

The economic literature has examined how extreme weather events affect economic outcomes (Dell et al., 2014), and how economic and financial markets' impacts of physical and transition risks related to climate change can vary according to geography, economic sector and by economic and financial system development (Basel Committee on Banking Supervision, 2021). Lately, growing efforts have emerged to quantify the impact of climate change risks on the financial sector and for individual institutions (Vermeulen et al., 2018; Allen et al., 2020; Baudino and Svoronos, 2021; Bank of England, 2021b,a). In fact, in 2017 a group of central banks and financial supervisors created the Network for Greening the Financial System (NGFS) with the purpose of contributing to the development of environmental and climate risk management in the financial sector.

This paper contributes to an emerging literature that focuses on the impact of rainfall on banks' balance sheet, specifically on banks' lending capacity and loan losses. My results are aligned with those of Bayangos et al. (2021) who found immediate effects on banks' loan growth and loan quality, while Cortés and Strahan (2017) found that most of the impacts on banks occur in the two quarters following a rainfall shock. As for the direction of the impacts on lending, my results are consistent with those of Keerthiratne and Tol (2017) who found that companies and households increase their indebtedness after a natural disaster. Similarly, Collier (2014) found an increase in commercial bank lending to their clients when analysing the behavior of micro, small, and medium-sized enterprise lenders in Peru during severe flooding episodes. Furthermore, Koetter et al. (2020) found that during the 2013 Elbe floods in Germany, local banks linked to the flooded firms increase lending, mitigating the effects of the shocks on the industry sector.

Regarding the effect on loan losses, several studies have analyzed the effects on non-performing loans (Dowla, 2018; Brei et al., 2019; Bayangos et al., 2021). Results vary across studies. Brei et al. (2019) suggest that, after hurricane strike, there are no signs of deterioration in loan defaults for Eastern Caribbean banks. But, there is a negative effect on deposit withdrawals to which banks respond, periods after, by reducing the supply of lending and by drawing on liquid assets. In contrast, Dowla (2018) reports that a quarter of borrowers in Bangladesh defaulted after severe floods in 1987 and required government bailout to recover. However, this paper is more related to Zhang et al. (2021) who use loan provisions to measure the bank loss. They found that, in a natural disaster scenario, banks need to increase loan provisions to ensure normal operations.

In Colombia, the effects of weather shocks have been studied mainly on formal rural employment outcomes (Bohorquez-Penuela et al., 2020) and on the number of credits granted to the agricultural sector (Bohorquez-Penuela, 2021). Few others have analysed the effects of weather variability on credit scores and credit access to coffee farmers (De Roux, 2020). Furthermore, the SFC and the World Bank recently published a report identifying relevant physical and transition risks with a focus on the banking sector. Considering the effects on credit risk in the loan portfolio, it is found that flood scenarios can lead to declines in capital adequacy ratio (World Bank, 2021). To date, the literature in Colombia has not explored the direct effect of rainfall shocks and rainfall variability on bank loans by credit modality. Therefore, this paper aims to contribute by analysing the effect on commercial, consumer, housing and microcredit loans, and the heterogeneous effects depending on banks' exposure to vulnerable sectors.

The rest of the paper is organized as follows. Section 2 provides a theoretical framework and section 3 summarizes the data sources. Section 4 describes the identification strategy, section 5 reports the main findings, and section 6 concludes.

2 Context

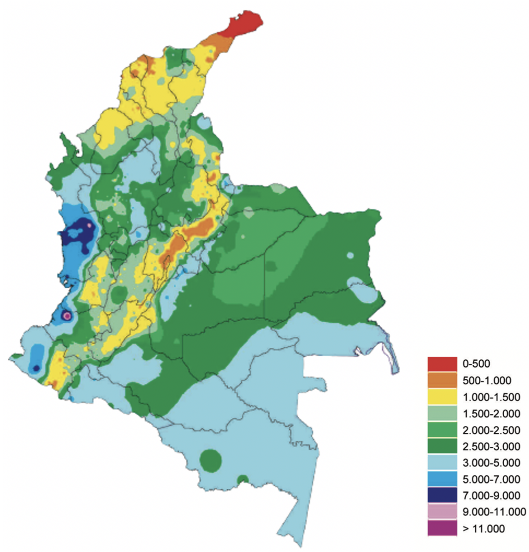
2.1 Rainfall Patterns in Colombia

According to IDEAM[4], Colombia is one of the most pluviometric-diverse nations in the world, which means that the monthly distribution of rainfall varies throughout the territory. The frequency of El Niño–Southern Oscillation (ENSO) is between 3 and 7 years, and during these processes changes in rainfall patterns are observed. For instance, El Niño phenomenon causes a decrease in rainfall and an increase in temperatures, especially in the Andean and Caribbean regions. Meanwhile, La Niña phenomenon causes an increase in rainfall and lower temperatures in much of the country.

[4]http://atlas.ideam.gov.co/cclimatologicas/info/lluviamen.html

The distribution of rainfall in Colombia varies across regions, and within regions, it varies across time and location. Figure 1 depicts the distribution of the annual average rainfall. In the far north of the Caribbean region[5] yearly average rainfall oscillates between 300 and 600mm, while in the southern area yearly average rainfall rounds between 1,800 and 2,000mm. However, during April and June, and between September and December this region experiences two well-defined rainy seasons.

Figure 1: Distribution of the annual average rainfall



The figure depicts the distribution of the annual average rainfall in Colombia. Source: IDEAM.

The average intensity of rainfall of the Andean region[6] varies by latitude. In the areas located at the bottom of the valleys it is less than 1,200mm, while in the others it varies between 2,000 and 4,000mm. In the southern area, the driest season takes place during mid-year, and in the northern area it takes place during December, January, and February. As in the Andean region, the average intensity of rainfall in the Orinoquia region[7] varies across its area (between 1,500 and 6,000mm). However, between late-March and November rainfall is abundant and widespread.

Finally, the Amazon[8] and Pacific[9] regions are the rainiest areas in Colombia. In the Pacific region, yearly average rainfall lies between 8,000 and 10,000mm, and there are not clear seasonal patterns in rainfall. Meanwhile, between April and November the

[5] The Caribbean region is located in the north of Colombia and comprises the departments of Atlántico, Bolívar, Cesar, Sucre, Córdoba, Magdalena, La Guajira and San Andrés and Providencia.

[6] The Andean region is located across the main lands of the Andes range and comprises the departments of Antioquia, Boyacá, Caldas, Cundinamarca, Huila, Norte de Santander, Quindío, Risaralda, Santander and Tolima.

[7] The Orinoquia region is located to the east of the Andes range and comprises the departments of Arauca, Casanare, Meta and Vichada

[8] The Amazon region is located in southern Colombia and comprises the departments of Amazonas, Caquetá, Guainía,

[9] The Pacific region is bordered by the Pacific Ocean to the west and the West Andes to the east, and comprises the departments of Amazonas, Putumayo, Caquetá, Guainía, Guaviare, and Vaupés, as well as sections of the departments of Cauca, Meta, and Vichada.

Amazon region experiences the wettest season (yearly average rainfall between 3,000 and 4,500mm).

During July and November 2010, the cooling observed in the surface ocean water along the Pacific Ocean affected the patterns of rainfall, increasing rainfall intensity in much of the country IDEAM (2012). These two months were the rainiest in the last 40 years, and the highest amount of rainfall were registered in the Caribbean, Andean and Pacific regions. As it was mentioned above, the driest season in the Andean region takes place during mid-year, however as a result of La Niña phenomenon in 2010, the recorded amount of rainfall exceeded the historical averages in this region, as well as in the Caribbean region. Likewise, even though in February the amount of rainfall normally decreases, during 2010 the recorded amounts of rainfall exceeded the monthly averages in most of the Andean, Caribbean, Orinoquia and Pacific regions.

According to Cepal et al. (2013), during La Niña event in 2010-2011 total losses reached around US$7.0 billion (2.0 percent of the 2011 gross domestic product). The total losses in the agricultural sector represented 36.8% of the total losses, and were mainly due to the decrease in income from crops. Losses in the mining sector represented 29.1%, and transportation sector registered 20.1% of total losses (Table 1). The departments that concentrated the highest level of losses were: Antioquia, Bolívar, Córdoba, Cundinamarca, Santander, Sucre and Valle del Cauca.

Table 1: Losses by economic sector during La Niña phenomenon in 2010 and 2011

Economic sectors	2010	2011	Total	Share of losses	% of sector GDP
Agriculture	418,250	344,844	763,094	36.8	2.1
Mining	608,000	-	608,000	29.3	1.4
Transportation	142,699	275,063	417,762	20.1	1.2
Tourism	125,914	32,861	158,775	7.7	0.1
Real Estate	46,383	46,383	92,765	4.5	0.2
Electricity	17,220	4,368	21,588	1.0	0.1
Services	6,069	6,069	12,138	0.6	0.0
Total	1,364,534	709,588	2,074,122	100	0.4

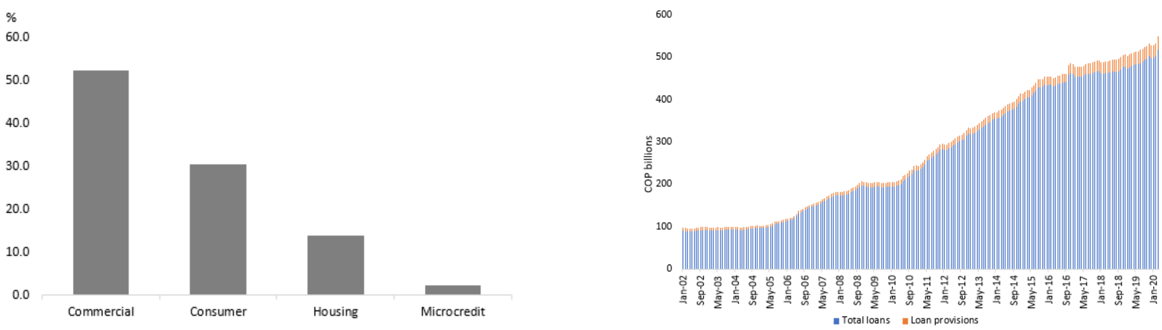
The table depicts estimated losses by economic sector during La Niña phenomenon in 2010 and 2011. Losses units in Col$ million, constant 2011 consumer price index. Source: CEPAL.

2.2 The Colombian banking sector

Colombia has a relatively large banking sector compared to its peers in Latin America. By December 2019, the banking system accounted for 33.6% of total assets of the financial system (Financial Superintendence of Colombia, 2020). As for the composition of the asset, a large percentage of total bank assets, around 63%, correspond to the credit portfolio, which consists primarily of commercial and consumer loans (Figure 2a). Regarding loan provisions, Figure 2b depicts the total amount of banks' loans and loan provisions for 2002–2020. By December 2019, loan provisions to total loans ratio was around 6%.

Figure 2: Banks' total credit portfolio and loan provisions

(a) Total credit portfolio composition (b) Total credit portfolio and loan provisions



Panel A depicts banks' credit portfolio composition by December 2019 and Panel B banks' total portfolio and loan provisions for the period 2002–2020. Source: Financial Superintendence of Colombia.

Historically, the commercial credit portfolio has been mainly comprised by manufacturing, trade and construction sectors (Figure 3). However, about 20% of total portfolio is comprised toward economic sectors that are considered vulnerable to climate change: agriculture, mining, transportation and electricity. Changes in temperature, rainfall, and droughts can have an important impact on the market value and creditworthiness of these sectors. Therefore, the Colombian banking sector is, to some extent, exposed to climate-related natural disasters.

3 Data

This paper uses two different data sources. Regarding loans, the data comes from the SFC. This dataset is at bank-quarter-municipal-level, and contains information for the period 2002q1–2020q1[10] on the gross total portfolio, and loan provisions by type of loans: commercial, consumer, housing and microcredit. As for loans granted to economic sectors[11], data also comes from the SFC. This data set is at bank-quarter-level, and contains information on total portfolio by sector.

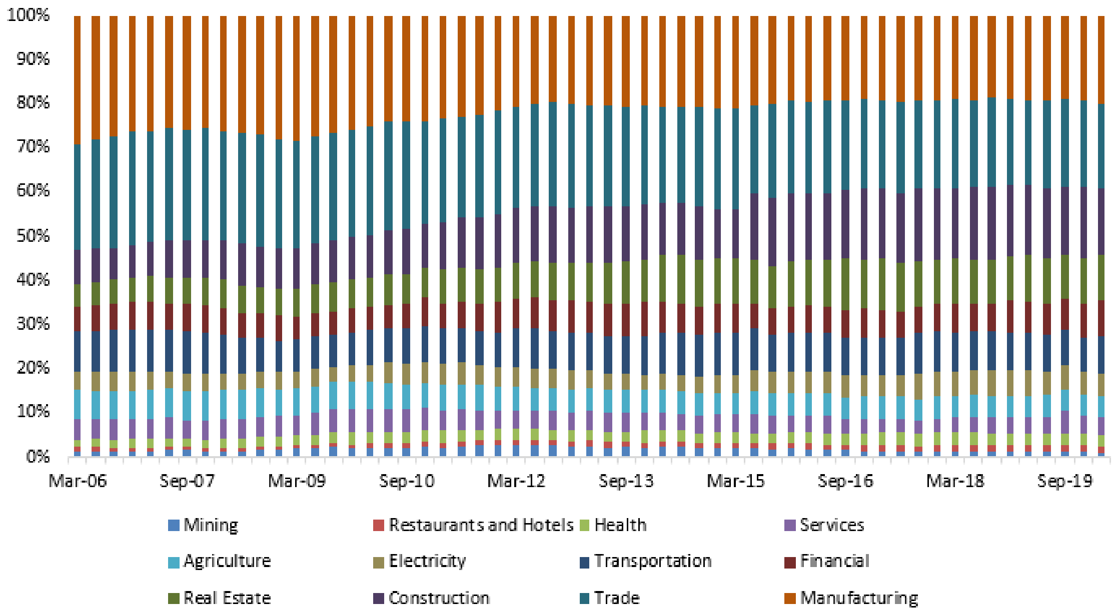
Regarding weather, the dataset comes from the IDEAM, and contains information on rainfall registered by more than 2,000 weather stations in Colombia[12]. Rainfall is measured in millimeters (1 litre per square metre of water on the surface), and is quar-

[10]Data after 2020q1 is not included since in 2020q2 credit institutions set up an additional general provision based on an estimate of the potential deterioration in the loan portfolio associated with the effects of the COVID-19 pandemic (SFC - Cicular Externa 022 de 2020)

[11]Economic sectors included are: mining, agriculture, real estate, restaurants and hotels, electricity, construction, health, transportation, trade, services, financial and manufacturing.

[12]Since 1900 the IDEAM has collected weather data on rainfall and temperatures for 2,726 stations. However, throughout the years the number of stations has not been constant.

Figure 3: Banks' commercial credit portfolio



The figure depicts banks' commercial credit portfolio composition. Abbreviations are used for the following sectors: 1) real estate, rentals and business: real estate; 2) agriculture, animal husbandry, hunting, forestry, and fishing: agriculture; 3) mining and quarrying: mining; 4) electricity, gas and water: electricity; 5) transportation, warehousing, and communications: transportation; 6) financial intermediation: finance, and 7) public administration and defense; education; other community, social and personal service activities; private households with domestic servants, and extraterritorial entities: services. Source: Financial Superintendence of Colombia.

terly aggregated. Following Bohorquez-Penuela et al. (2020), one of the main weather measures corresponds to the logarithm of quarterly rainfall for each municipality, and the other two correspond to different indicator variables. The first one represents heavy rainfall shocks and is equal to one if the observed quarterly amount of rainfall is at or above the 80th percentile of the quarterly historical distribution for each municipality. The second one represents low rainfall shocks and is equal to one if the observed quarterly amount of rainfall is at or below the 20th percentile of the quarterly historical distribution. The historical distributions of rainfall are estimated using the rainfall observed in the municipality m for quarter q 30 years before the initial date of analysis.[13]. Therefore, to estimate quarterly weather shocks between 2002q1 and 2020q1, weather data is included since 1970. For those municipalities with more than one weather station, I calculate the average rainfall by municipality.

The resulting dataset, that is, the one that is generated after merging the weather data with loan portfolio information, generates an unbalanced panel that comprises 705 municipalities and an average of 30 banks by period (Figure A1). It is an unbalanced panel since, over the years, some banks have changed their type of credit institution, and some financial cooperatives and financing companies have become banks. Further-

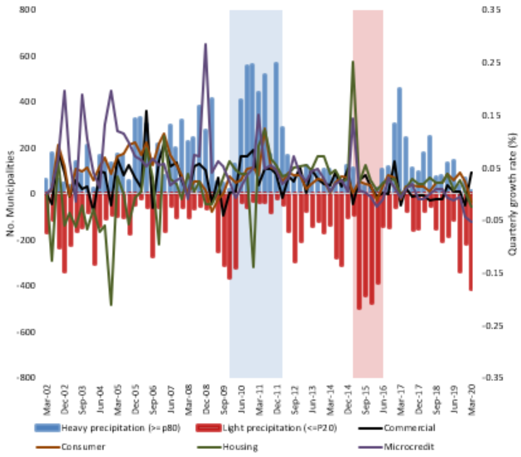
[13]The estimation of the historical distribution by municipality and by quarter is performed to account for seasonality

more, the total of municipalities included correspond to those in which there is a record on banks' loans information: in some cases (10%) banks are located in municipalities for which there is no weather station information. Therefore, to include those observations in the dataset, the closest municipality was imputed, however, in Appendix B, I also present the results without these imputations. In Figure 4, the distribution of rainfall shocks across time is presented, as well as the quarterly growth rates of the four type of loans analysed. During 2010-2011, more than half of the municipalities faced heavy rainfall shocks, and during 2015-2016 a large number of municipalities faced low rainfall shocks. The former coincides with the La Niña phenomenon experienced in Colombia during 2010-2011, and the latter with the El Niño phenomenon in 2015.

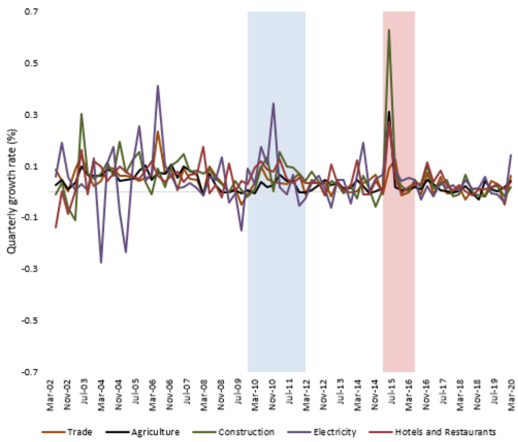
As for the dynamics of the loan portfolio, during 2010-2011 a positive growth rate is observed for the commercial, consumer and microcredit loans, contrary to what is observed for the housing loans. In contrast, during 2015-2016 a slow-down in the growth rate is observed for the four types of loans. Regarding the dynamics of the loan portfolio by economic sector, during La Niña phenomenon the quarterly growth rate in the agriculture, construction, electricity and hotels and restaurants reached a peak.

Figure 4: Distribution of rainfall shocks and quarterly growth rate of loans

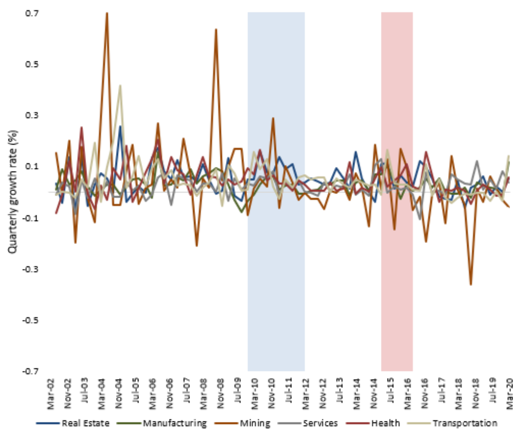
(a) Total loans by credit modality



(b) Total loans by economic sector



(c) Total loans by economic sector



The figure depicts the distribution of rainfall shocks and quarterly growth rate of loans by credit modality and economic sector. Blue bars correspond to the total amount of municipalities facing a heavy rainfall shock at each date. Red bars correspond to the total amount of municipalities facing a low rainfall shock at each date. Heavy rainfall shocks are determined by an indicator variable equal to one if the observed quarterly amount of rainfall is at or above the 80th percentile of the quarterly historical distribution for each municipality. Low rainfall shocks are determined by an indicator variable equal to one if the observed quarterly amount of rainfall is at or below the 20th percentile of the quarterly historical distribution. Light blue shaded ares correspond to La Niña phenomenon in 2010, and light red shaded areas correspond to El Niño phenomenon in 2015. Source: Financial Superintendence of Colombia and IDEAM.

4 Empirical Strategy and Specification

To investigate the extent to which increases in rainfall and transitory rain shocks lead banks to modify their provisions and loans, I follow Jayachandran (2006) and

Bohorquez-Penuela et al. (2020). The specification model relies on bank, municipality and quarter fixed effects:

$$Y_{i,m,q,t} = \beta_0 + \beta_1 W^+{}_{m,q,t} + \beta_2 W^+{}_{m,q,t-1} + \beta_3 W^-{}_{m,q,t} + \beta_4 W^-{}_{m,q,t-1} \\ + \delta t + \gamma_m + \theta_q + \alpha_i + \epsilon_{i,m,q,t} \quad (1)$$

where $Y_{i,m,q,t}$ corresponds to the outcome of interest (total portfolio by type of loans in logarithms and provisions to total loans ratio by type of loans), i denotes banks, m denotes municipality, t stands for year, and q for quarter. W^+ and W^- account for current (q, t) and lagged $(q, t-1)$ realizations of heavy and low rainfall shocks, in its order. These two measures of rainfall shocks are described in Section 3. Firstly, the logarithm of present and past values of rainfall is included as the main weather measure. Thereafter, the indicator variables of heavy and low rainfall shocks are considered as the variables of interest. Variable t corresponds to an annual linear trend that accounts for the passage of time. In this regard, I also analyse the results including year fixed effects instead of the annual linear trend. α_i, γ_m and θ_q are the bank, municipality and quarter fixed effects, in its order. Errors $\epsilon_{i,m,q,t}$ are clustered at the municipality level. The parameters of interest are β_1, β_2, β_3, and β_4, since they intend to capture the effect of current and past weather shocks on total loans and provisions.

To investigate the role of commercial loan portfolio composition, I examine if the effect of rainfall shocks on the commercial credit portfolio varies with banks' exposure to different economic sectors. In particular, I want to estimate the following specification:

$$Y_{i,m,q,t} = \phi_0 + \phi_1 W^+{}_{m,q,t} \times X_{i,s} + \phi_2 W^+{}_{m,q,t-1} \times X_{i,s} + \phi_3 W^-{}_{m,q,t} \times X_{i,s} + \phi_4 W^-{}_{m,q,t-1} \times X_{i,s} \\ + \delta t + \gamma_m + \theta_q + \alpha_i + \epsilon_{i,m,q,t} \quad (2)$$

where $X_{i,s}$ corresponds to an indicator variable equal to 1 if the share of the loan portfolio of bank i granted to the economic sector s is greater than the observed average share of all banks before 2010 (year in which more than half of the municipalities included in the sample faced heavy rainfall episodes). In this regard, Table 2 shows the total number of banks whose commercial portfolio is highly exposed to each of the listed economic sectors. Column (1) identifies if a bank is exposed by comparing the share of the loan portfolio of bank i granted to the economic sector s with the average share of all banks. Column (2) compares the individual share with the median participation of all banks. As can be seen, when the median is used, a greater number of banks are identified as exposed in sectors whose aggregate share to commercial portfolio is low (i.e. financial, agriculture, electricity, restaurants and hotels, services and transportation). The parameters of interest are ϕ_1, ϕ_2, ϕ_3, and ϕ_4, since they capture the differential impact of rainfall among banks with high exposure to economic sector s.

Table 2: Total banks with high exposure to each economic sector

Economic Sector	(1) Average share measure		(2) Median share measure	
	No. Banks	Share	No. Banks	Share
Financial	10	32.3	12	38.7
Agriculture	7	22.6	14	45.2
Trade	16	51.6	14	45.2
Construction	8	25.8	13	41.9
Electricity	10	32.3	13	41.9
Restaurants and Hotels	9	29.0	14	45.2
Real Estate	10	32.3	12	38.7
Manufacturing	13	41.9	13	41.9
Mining	13	41.9	6	19.4
Services	8	25.8	14	45.2
Health	13	41.9	13	41.9
Transportation	12	38.7	14	45.2

The table depicts the total number of banks whose share of the loan portfolio granted to each economic sector is greater than the observed average share (column 1) and median share (column 2) of all banks before 2010, year in which more than half of the municipalities included in the sample faced heavy rainfall episodes. Source: Financial Superintendency of Colombia.

To claim a causal effect of the estimates several aspects are considered. The inclusion of municipality-level fixed effects is done to control for the heterogeneity of rainfall patterns along the country[14], and quarter fixed effects are included to address unobserved time-variant characteristics. Moreover, I include bank-level fixed effects to control for bank-specific factors that could be related with banks' ability and willingness to provide credit (differences in credit supply).

As for measurement error on total loans and loan portfolio variables, even though this paper uses data from official registries, variables can be wrongly measured. However, this issue is not of great concern since measurement error in the dependent variable implies that estimates would remain unbiased. Regarding weather, as there are at least more than one weather station per municipality, I control for measurement error by using the average amount of rainfall of all weather stations per municipality, which helps increasing accuracy on the explanatory variable.

5 Results

5.1 Effects by municipality

I begin by investigating the effects of rainfall on total loans. Table A1 depicts estimates of current, lagged, and both present and past levels of the logarithm of rainfall (Equation 1). Columns 1-3, 7-9, 13-15, and 19-21 include an annual linear trend, while

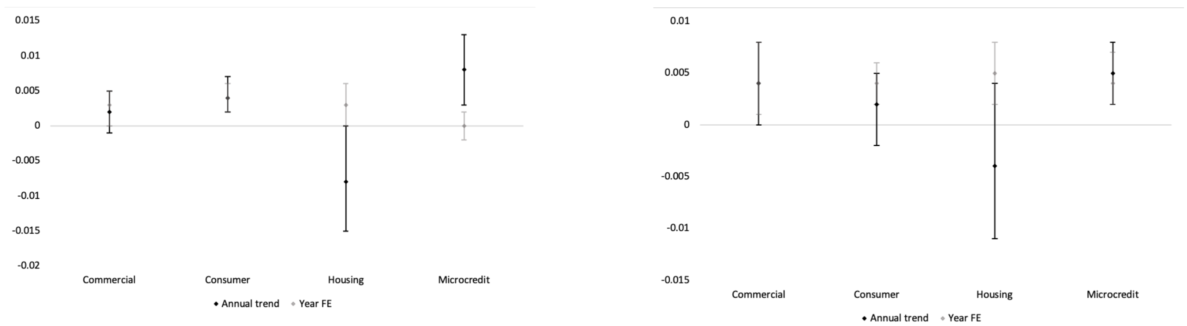
[14]See Section 3

the remainders include year fixed-effects. In general, these estimates give information on the direction of the effect of increases in the level of rainfall. Figure 5 depicts these estimates and their 90 percent confidence intervals. As for immediate effects, when analysing the results that include an annual linear trend, I find a statistically significant and positive effect on the consumer and microcredit portfolio, and negative effect on the housing portfolio. These results only hold for consumer loans when time fixed effects are included, and for housing loans estimates appears to be statistically significant and positive (Figure 5.a). Considering lagged effects ($Log(Rainfall)_{t-1,q}$), in general, for all type of loans estimates are statistically significant and positive.

Figure 5: Effects of quarterly rainfall on total loans by credit modality

(a) Current Log(Rainfall) levels

(b) Lagged Log(Rainfall) levels

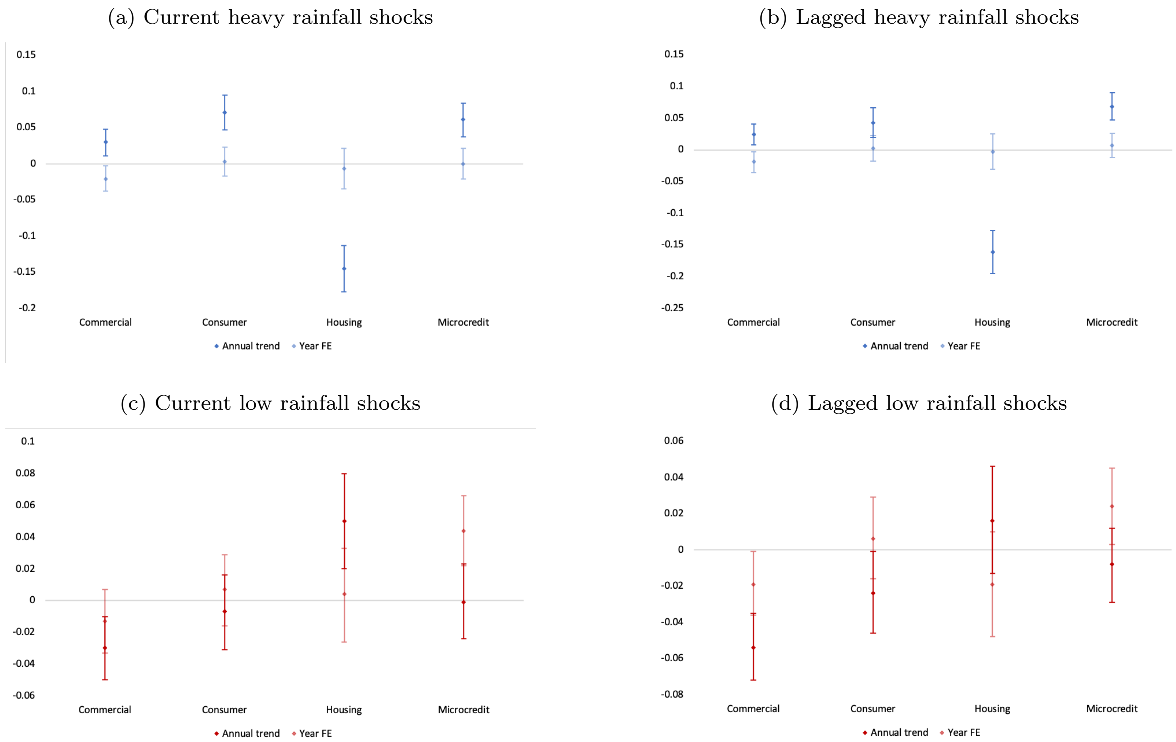


The figure depicts the estimates presented in Table A1: the effects of the current and lagged levels of the logarithm of rainfall on total loans by credit modality. 90 percent confidence intervals.

Regarding the effects of rainfall shocks on the banks' portfolio, Table A2 reports the estimates for Equation 1 using rainfall shocks as the weather measures: heavy rainfall shocks refer to $RainShock[Rainfall \geq 80th]$ and low rainfall shocks to $RainShock[Rainfall \leq 20th]$. Columns 1-3, 7-9, 13-15, and 19-21 include an annual linear trend, while the remainders include year fixed-effects. Figure 6 depicts these estimates and their 90 percent confidence intervals. Overall, current heavy rainfall shocks have a positive impact on consumer and microcredit loans, and a negative impact on housing loans. The direction of these estimates remain the same when year fixed effects are included, however estimates are not statistically significant. Regarding the commercial portfolio, results vary among the different specifications. All in all, these results coincide with the ones that measure the effects of lagged heavy rainfall shocks.

As for current low rainfall shocks, I find a positive impact on housing loans, while the effect is negative on commercial loans, and zero on consumer and microcredit loans. When year fixed effects are included, results are the same in direction but not statistically significant for housing and commercial loans, and for microcredit loans a positive and statistically significant effect is found. Regarding the lagged realization of low rainfall shocks, past shocks have a statistically significant and negative impact on commercial and consumer loans.

Figure 6: Effects of rainfall shocks on total loans by credit modality



(a) Current heavy rainfall shocks

(b) Lagged heavy rainfall shocks

(c) Current low rainfall shocks

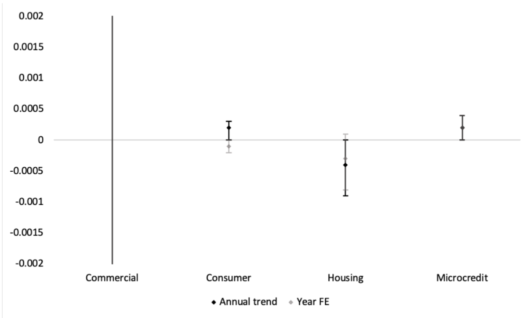
(d) Lagged low rainfall shocks

The figure depicts the estimates presented in Table A2: the effects of the current and lagged rainfall shocks on total loans by credit modality. 90 percent confidence intervals.

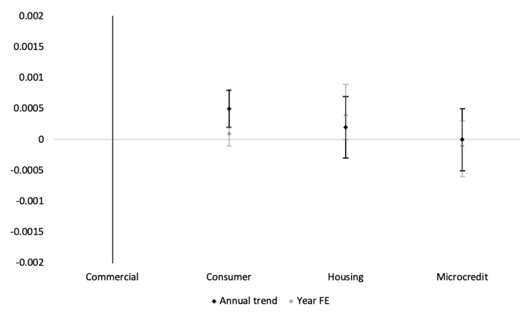
Considering the effects on loan provisions, Table A3 shows estimates of equation (1) using loan provisions to total loans ratio as the dependent variable. Figure 7 depicts these estimates and their 90 percent confidence intervals. Regarding changes in present levels, the effect is negative for housing loan provisions, and positive for consumer loan provisions. Regarding lagged realizations of rainfall, I find a statistically significant and positive effect only on consumer loan provisions. More interestingly, Table A4 depicts the effects of rainfall shocks on loan provisions to total loans ratio, and Figure 8 depicts these estimates and their 90 percent confidence intervals. Episodes of heavy rainfall lead to increases in loan loss provisions for the consumer portfolio, and to decreases for the housing portfolio. These results remain the same when year fixed effects are included. The effects of lagged episodes of excess rainfall are statistically significant and positive only on consumer loan provisions.

Figure 7: Effects of quarterly rainfall on total loan provisions by credit modality

(a) Current Log(Rainfall) levels



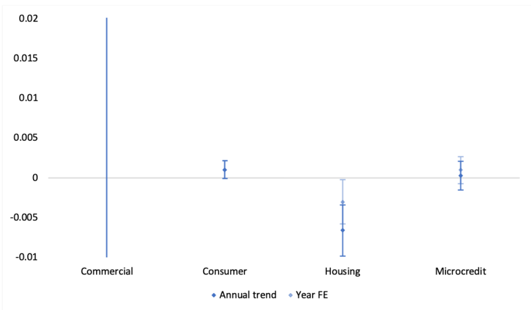
(b) Lagged Log(Rainfall) levels



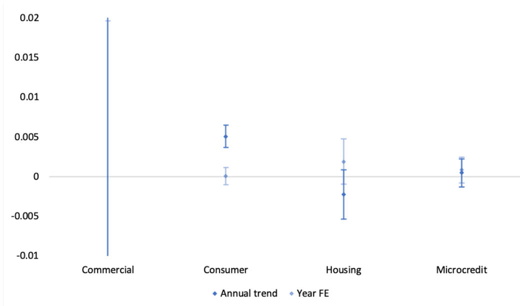
The figure depicts the estimates presented in Table A3: the effects of the current and lagged levels of the logarithm of rainfall on total loan provisions by credit modality. 90 percent confidence intervals.

Figure 8: Effects of rainfall shocks on total loan provisions by credit modality

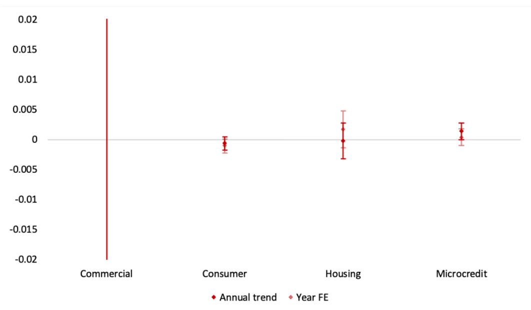
(a) Current heavy rainfall shocks



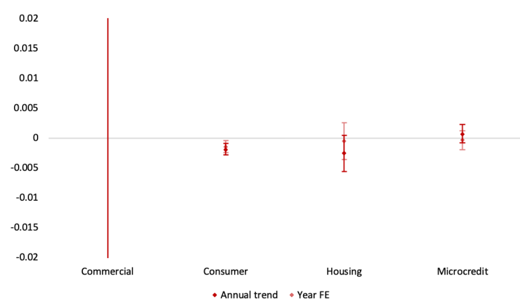
(b) Lagged heavy rainfall shocks



(c) Current low rainfall shocks



(d) Lagged low rainfall shocks



The figure depicts the estimates presented in Table A4: the effects of the current and lagged rainfall shocks on total loan provisions by credit modality. 90 percent confidence intervals.

In summary, the estimates from Tables A1 and A2 (Figures 5 and 6) show that episodes of heavy rainfall during quarter q have an immediate effect on the consumer, housing and microcredit portfolio. Consumer and microcredit loans increase, while housing loans decrease. These results are related to the fact that those periods in which a large number of municipalities are facing an episode of heavy rainfall [15] coincide with an increase in the banks' demand-perception indicator for the consumer, commercial and microcredit loans (Fernández-Moreno et al., 2011). Furthermore, according to Del Ninno et al. (2003), it is highly likely that the credit demand increases after a climate event in order to cope with higher food prices and lower incomes from employment disruptions. In this regard, given that the SFC defines the consumer portfolio as credits granted to a natural person to finance the purchase of consumer goods, and the microcredit portfolio as loans granted to small and medium enterprises, the positive effect on the consumer and microcredit portfolio is due to the fact that, during an episode of heavy rainfall, individuals could face a negative income shock (Bayudan-Dacuycuy and Baje, 2019; Bohorquez-Penuela et al., 2020). Therefore, to cope with this, individuals resort to credit. On the contrary, the housing portfolio is defined as loans granted to a natural person for the purchase of new or used housing. Thus, the negative effect on the housing portfolio is due to the fact that, in a scenario in which individuals face an income shock and prices rise, buying a house may not be a priority as it is to satisfy basic needs.

As for low rainfall, results are mixed and estimates vary between the model with annual linear trend and the model with time fixed effects. However, it is worth looking at the effects on housing and commercial loans, as the results are the same in direction but not statistically significant when year fixed effects are included: housing loans increase and commercial loans decrease. This is perhaps related to the fact that episodes of low rainfall are not associated with an income shock, thus individuals do not need to resort to credit to cope with higher food prices and lower incomes.

Regarding the effect of rainfall shocks on loan loss provisions ratio, the estimates from Tables A3 and A4 (Figures 7 and 8) show that the consumer loan provisions increase to episodes of heavy rainfall, while the housing loan provisions decrease. Jointly with the results presented above, these results suggest that counterparty risk (i.e. the risk that a borrower failure to repay a loan or meet contractual obligations) is increasing for the consumer portfolio and decreasing for the housing portfolio. The fact that the consumer portfolio increases to heavy rainfall shocks and that consumer loan provisions also increase suggests that the banks are probably lending money to risky borrowers (classification other than A), which, according to SFC, requires banks to increase provisions more than proportional to total loans. Similarly, the housing loan provisions decrease since the housing portfolio also decreases to high rainfall shocks.

Another possible explanation is related to the effect of loan restructuring on total provisions. Loan restructuring refers to changing existing loan contract terms for the borrower. This process may involve either lower interest rates on loans or an extension of the period when the debtor's payments are due to be paid. Loan restructuring implies a reclassification of loans' risk rating, and therefore gives rise to make loan provisions (Financial Superintendence of Colombia, 1995). According to Collier et al. (2011) excess rainfall significantly increases problem loans, specifically the level of restructured loans.

[15] See Figure 4

Prior to loan restructuring comes loan modification, however, if the loans have already been modified, then banks can only apply a loan restructuring process. Historically, the quarterly percentage of modified loans in the consumer portfolio has been higher than the loan modifications of the other type of loans (López-Daza et al., 2020). Therefore, it seems likely to consider that heavy rainfall increases consumer loan provisions as the number of restructuring loans increase.

In Tables B1 to B4, I present these results using a data set in which there is no imputation of the closest municipality for those banks located in municipalities for which there is no weather station information. Estimates results remain practically the same.

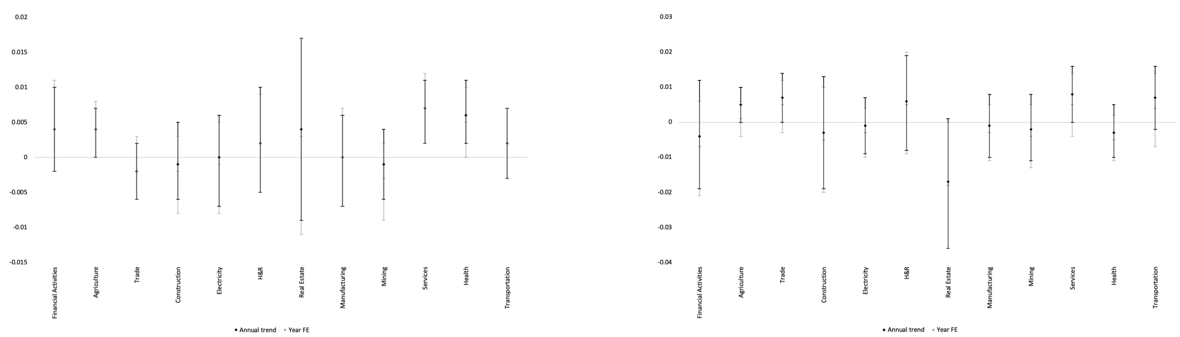
5.2 Effects by economic sector

In this section I examine if the effect of the rainfall shocks on the commercial loan portfolio varies with banks exposure to different economic sectors. As mentioned above, to investigate the heterogeneous effects, an indicator variable $X_{i,s}$ is included. This variable is equal to 1 if, for the bank i, the share of the portfolio of the sector s is higher than the average share of the economic sector s portfolio registered before 2010. Tables A5 and A6 depict estimates of current, lagged, and both present and past levels of the logarithm of rainfall (Equation 2). Columns 1-3 include an annual linear trend, while the remainders include year fixed-effects. In general, these estimates give information on the direction of the effect of increases in the level of rainfall. Figure 9 depicts these estimates and their 90 percent confidence intervals. For banks with a high participation in the agricultural, services and health sectors, I find a statistically significant and positive effect on commercial loans. These results remain the same when year fixed effects are included.

Figure 9: Effects of quarterly rainfall on commercial loan portfolio by economic sector

(a) Current Log(Rainfall) levels

(b) Lagged Log(Rainfall) levels

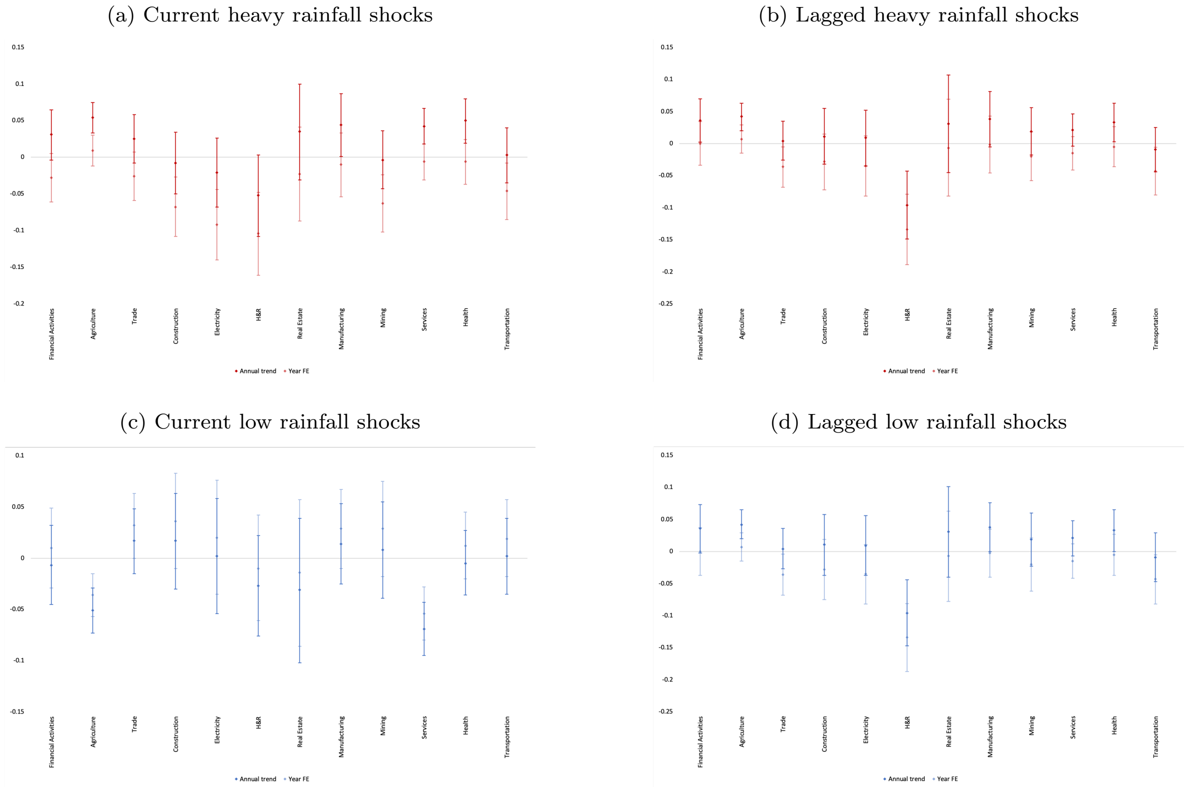


The figure depicts the estimates presented in Table A5: the effects of the current and lagged levels of the logarithm of rainfall on commercial loan portfolio by economic sector. 90 percent confidence intervals.

As for the effects of rainfall shocks (Figure 10), current heavy rainfall shocks increase the commercial loan portfolio for banks with a high participation in the agricultural, services, health and manufacturing sectors. The direction of these estimates remain the same (except for the manufacturing sector) when year fixed effects are included, however estimates are not statistically significant. Meanwhile, current low rainfall shocks decrease the commercial loan portfolio for banks with a high participation in the agricultural and services sectors. The results remain the same in direction and statistical significance when year fixed effects are included.

Regarding the agricultural sector, Bohorquez-Penuela (2021) finds that La Niña phenomenon in Colombia is associated with an increase on the number of credits granted (3.4 percent). In fact, total credit, as well as the number of credits granted and the average value of the credit per beneficiary tend to increase around the beginning of El Niño and La Niña events for the period 2002–2019. Moreover, the increase in the commercial loan portfolio for banks with a high participation in the agricultural sector can be explained by the fact that those periods in which a greater number of municipalities face a higher level of rainfall coincide with periods of high losses for this sector (See Section 2). Therefore, it is highly likely that the demand for credit increases to cope with economic losses.

Figure 10: Effects of quarterly rainfall shocks on commercial loan portfolio by economic sector



The figure depicts the estimates presented in Table A6: the effects the current and lagged rainfall shocks on commercial loan portfolio by economic sector. 90 percent confidence intervals.

Finally, in Tables C1 to C4 I present estimates of equation (2) using $X_{i,s}$ as an indicator variable equal to 1 if for the bank i the share of the portfolio of the sector s is higher than the median share of the economic sector s portfolio registered before 2010. The results remain practically the same.

6 Concluding Remarks

This paper analyses the effect of rainfall and rain shocks on banks' portfolio and loan provisions. First, the results on banks' portfolio suggest that episodes of heavy rainfall increase consumer and microcredit loans and decrease housing loans. These results points out that, during an episode of heavy rainfall, individuals could face a negative income shock, thus to cope with this, they resort to credit. Households resort to consumer loans, and small and medium enterprises (small businesses) resort to microcredit loans. Furthermore, since buying a house may not be a priority as it is to satisfy basic needs, housing loans decrease.

Second, the results on banks' loan provisions suggest that the consumer loan provisions increase to episodes of heavy rainfall, while the housing loan provisions decrease. This is explained, on the one hand, by counterparty risk. The increase in both the consumer portfolio and consumer loan provisions suggests that the banks are probably lending money to risky borrowers (classification other than A), which increases banks' consumer loan provisions. Likewise, the housing loan provisions decrease as the housing portfolio shrinks, since banks are not lending to borrowers with different risk profiles. On the other hand, as loan restructuring gives rise to make loan provisions, and the quarterly percentage of modified loans in the consumer portfolio is higher than the loan modifications of the other type of loan, it seems likely that heavy rainfall increases consumer loan provisions as the number of restructuring loans increase.

Finally, considering that losses associated with climate-related risks are increasingly affecting the financial sector globally and locally, it is essential to keep investigating on climate-related risks in the Colombian banking sector. Empirical investigation is needed to shed more light on potential effects of rainfall shocks on the financial system. The availability of data for all potential channels that affect the financial sector is a limitation, however different techniques are being developed to overcome this issue. In this paper the effect of rainfall on restructuring loans and non-performing loans is not being analyzed due to lack of information at a municipality-level.

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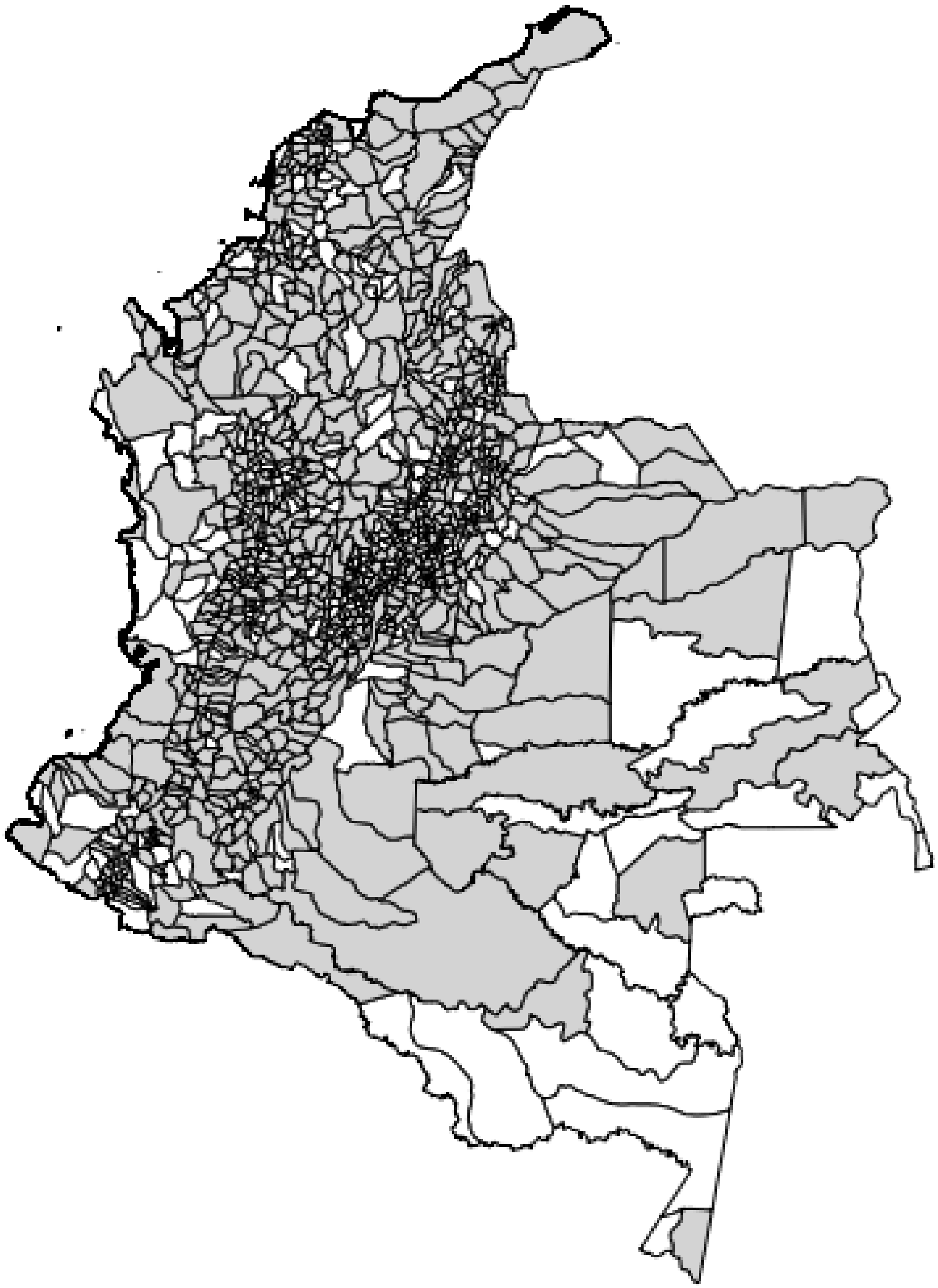
Appendix A:

Figure A1: Municipalities included in the sample



The figure depicts the municipalities (710) included in the loan portfolio-weather merged data set. There is no bank without an associated municipality since the closest municipality was imputed to the banks located in areas with a lack of information on the amount of quarterly rainfall.

Table A1: Effects of quarterly rainfall on total loans

	Log(Commercial)						Log(Consumer)						Log(Housing)						Log(Microcredit)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Log(Rainfall)	0.002		-0.000	0.003**		0.002	0.004***		0.003**	0.004***		0.003***	-0.008**		-0.008**	0.003**		0.001	0.008***		0.007***	-0.000		-0.002
	(0.002)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.004)		(0.004)	(0.001)		(0.002)	(0.003)		(0.003)	(0.001)		(0.002)
L.Log(Rainfall)		0.004*	0.004**		0.004**	0.003		0.002	0.000		0.004***	0.002		-0.004	0.000		0.005***	0.004**		0.005***	0.001		0.004**	0.005**
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)		(0.001)	(0.001)		(0.004)	(0.003)		(0.001)	(0.002)		(0.002)	(0.001)		(0.001)	(0.002)
Observations	113,256	102,651	102,651	113,256	102,651	102,651	108,751	98,551	98,551	108,751	98,551	98,551	75,786	68,689	68,689	75,786	68,689	68,689	89,157	81,609	81,609	89,157	81,609	81,609
Municipalities	695	688	688	695	688	688	695	689	689	695	689	689	657	643	643	657	643	643	696	688	688	696	688	688
R-squared	0.754	0.763	0.763	0.758	0.766	0.766	0.840	0.844	0.844	0.843	0.847	0.847	0.798	0.806	0.806	0.812	0.817	0.817	0.739	0.746	0.746	0.756	0.757	0.757
Year FE	NO	NO	NO	YES	YES	YES	NO	NO	NO	YES	YES	YES	NO	NO	NO	YES	YES	YES	NO	NO	NO	YES	YES	YES

The table depicts estimates of equation (1) using the logarithm of present and past values of rainfall as the weather measure. Dependent variable in constant COP $ (Base: Dec 2018=100). The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table A2: Effects of rainfall shocks on total loans

	Log(Commercial)				Log(Consumer)				Log(Housing)				Log(Microcredit)			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
RainShock[Rainfall≥80th]	0.030***		-0.021**		0.071***		0.003		-0.145***		-0.007		0.061***		0.000	
	(0.010)		(0.009)		(0.012)		(0.010)		(0.016)		(0.014)		(0.012)		(0.011)	
RainShock[Rainfall≤20th]	-0.030***		-0.013		-0.007		0.007		0.050***		0.004		-0.001		0.044***	
	(0.010)		(0.010)		(0.012)		(0.012)		(0.015)		(0.015)		(0.012)		(0.011)	
L.RainShock[Rainfall≥80th]		0.024***		-0.019**		0.043***		0.002		-0.161***		-0.003		0.068***		0.007
		(0.008)		(0.008)		(0.012)		(0.010)		(0.017)		(0.014)		(0.011)		(0.010)
L.RainShock[Rainfall≤20th]		-0.054***		-0.019**		-0.024**		0.006		0.016		-0.019		-0.008		0.024**
		(0.010)		(0.009)		(0.012)		(0.011)		(0.015)		(0.015)		(0.010)		(0.011)
Observations	113,256	102,651	113,256	102,651	108,751	98,551	108,751	98,551	75,786	68,689	75,786	68,689	89,157	81,609	89,157	81,609
Municipalities	695	688	695	688	695	689	695	689	657	643	657	643	696	688	696	688
R-squared	0.754	0.763	0.758	0.766	0.840	0.844	0.843	0.847	0.798	0.806	0.812	0.817	0.739	0.746	0.756	0.757
Year FE	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES

The table depicts estimates of equation (1) using the quarterly indicators variables of rainfall above the 80th percentile and below the 20th percentile as the weather measure. Dependent variable in constant COP $ (Base: Dec 2018=100). The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table A3: Effects of quarterly rainfall on loan provisions to total loans ratio

	Commercial loan provisions					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log(Rainfall)	0.0100		0.0095	0.0028		0.0030
	(0.0107)		(0.0095)	(0.0036)		(0.0034)
L.Log(Rainfall)		0.0127	0.0075		0.0036	0.0019
		(0.0131)	(0.0081)		(0.0043)	(0.0025)
Observations	113,217	102,613	102,613	113,217	102,613	102,613
Municipalities	695	688	688	695	688	688
R-squared	0.0089	0.0098	0.0098	0.0090	0.0099	0.0099
Year FE	NO	NO	NO	YES	YES	YES

	Consumer loan provisions					
VARIABLES	(7)	(8)	(9)	(10)	(11)	(12)
Log(Rainfall)	0.0002***		0.0002**	-0.0001		-0.0001
	(0.0001)		(0.0001)	(0.0001)		(0.0001)
L.Log(Rainfall)		0.0005***	0.0004***		0.0001	0.0001*
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Observations	108,721	98,525	98,525	108,721	98,525	98,525
Municipalities	695	689	689	695	689	689
R-squared	0.2406	0.2678	0.2679	0.2584	0.2857	0.2857
Year FE	NO	NO	NO	YES	YES	YES

	Housing loan provisions					
VARIABLES	(13)	(14)	(15)	(16)	(17)	(18)
Log(Rainfall)	-0.0004*		-0.0004	-0.0003		-0.0001
	(0.0002)		(0.0002)	(0.0002)		(0.0002)
L.Log(Rainfall)		0.0002	0.0004		0.0004	0.0004
		(0.0003)	(0.0003)		(0.0002)	(0.0003)
Observations	75,728	68,633	68,633	75,728	68,633	68,633
Municipalities	657	643	643	657	643	643
R-squared	0.4695	0.4795	0.4795	0.4767	0.4861	0.4861
Year FE	NO	NO	NO	YES	YES	YES

	Microcredit loan provisions					
VARIABLES	(19)	(20)	(21)	(22)	(23)	(24)
Log(Rainfall)	0.0002		0.0002*	0.0002*		0.0002
	(0.0001)		(0.0001)	(0.0001)		(0.0001)
L.Log(Rainfall)		-0.0000	-0.0001		-0.0001	-0.0001
		(0.0003)	(0.0002)		(0.0002)	(0.0002)
Observations	89,009	81,468	81,468	89,009	81,468	81,468
Municipalities	696	688	688	696	688	688
R-squared	0.2162	0.2223	0.2223	0.2211	0.2272	0.2272
Year FE	NO	NO	NO	YES	YES	YES

The table depicts estimates of equation (1) using the logarithm of present and past values of rainfall as the weather measure. The dependent variable is measured as the total loan provisions to total loans ratio. The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table A4: Effects of rainfall shocks on loan provisions to total loans ratio

	Commercial loan provisions				Consumer loan provisions				Housing loan provisions				Microcredit loan provisions			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
RainShock[Rainfall≥80th]	-0.0534		-0.0253		0.0010*		0.0010*		-0.0066***		-0.0030**		0.0003		0.0010	
	(0.0449)		(0.0236)		(0.0006)		(0.0006)		(0.0016)		(0.0014)		(0.0009)		(0.0009)	
RainShock[Rainfall≤20th]	-0.0549		-0.1207		-0.0006		-0.0010*		-0.0002		0.0017		0.0014*		0.0004	
	(0.0827)		(0.1447)		(0.0006)		(0.0006)		(0.0015)		(0.0015)		(0.0007)		(0.0007)	
L.RainShock[Rainfall≥80th]		-0.0548		-0.0366		0.0051***		0.0001		-0.0022		0.0019		0.0005		0.0009
		(0.0502)		(0.0287)		(0.0007)		(0.0006)		(0.0016)		(0.0015)		(0.0009)		(0.0009)
L.RainShock[Rainfall≤20th]		-0.0910		-0.0964		-0.0019***		-0.0014***		-0.0025		-0.0005		0.0007		-0.0003
		(0.0798)		(0.0887)		(0.0005)		(0.0005)		(0.0016)		(0.0016)		(0.0008)		(0.0008)
Observations	113,217	102,613	113,217	102,613	108,721	98,525	108,721	98,525	75,728	68,633	75,728	68,633	89,009	81,468	89,009	81,468
Municipalities	695	688	695	688	695	689	695	689	657	643	657	643	696	688	696	688
R-squared	0.0089	0.0098	0.0090	0.0099	0.2406	0.2688	0.2584	0.2857	0.4697	0.4795	0.4768	0.4861	0.2162	0.2223	0.2211	0.2272
Year FE	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES

The table depicts estimates of equation (1) using the quarterly indicators variables of rainfall above the 80th percentile and below the 20th percentile as the weather measure. The dependent variable is measured as the total loan provisions to total loans ratio. The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table A5: Effects of quarterly rainfall on commercial loan portfolio by economic sector

	Log(Gross Commercial)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log(Rainfall)×I[Agriculture]	0.005***		0.004**	0.003		0.004**
	(0.002)		(0.002)	(0.002)		(0.002)
L.Log(Rainfall)×I[Agriculture]		0.007***	0.005*		0.003	0.001
		(0.003)	(0.003)		(0.003)	(0.003)
Observations	107,239	97,235	97,235	107,239	97,235	97,235
R-squared	0.761	0.770	0.770	0.766	0.774	0.774
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Services]	0.010***		0.007***	0.007**		0.007***
	(0.003)		(0.002)	(0.004)		(0.003)
L.Log(Rainfall)×I[Services]		0.012**	0.008*		0.009	0.005
		(0.005)	(0.004)		(0.006)	(0.005)
Observations	107,384	97,369	97,369	107,384	97,369	97,369
R-squared	0.760	0.769	0.769	0.764	0.772	0.772
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Electricity]	-0.002		0.000	-0.004		-0.001
	(0.003)		(0.003)	(0.003)		(0.004)
L.Log(Rainfall)×I[Electricity]		-0.001	-0.001		-0.004	-0.003
		(0.004)	(0.004)		(0.004)	(0.004)
Observations	106,515	96,509	96,509	106,515	96,509	96,509
R-squared	0.758	0.767	0.767	0.763	0.771	0.771
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Mining]	-0.003		-0.001	-0.006		-0.003
	(0.004)		(0.003)	(0.004)		(0.003)
L.Log(Rainfall)×I[Mining]		-0.004	-0.002		-0.006	-0.004
		(0.005)	(0.005)		(0.005)	(0.004)
Observations	106,435	96,692	96,692	106,435	96,692	96,692
R-squared	0.759	0.768	0.768	0.763	0.772	0.772
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Construction]	-0.002		-0.001	-0.004		-0.002
	(0.006)		(0.003)	(0.006)		(0.003)
L.Log(Rainfall)×I[Construction]		-0.004	-0.003		-0.007	-0.005
		(0.008)	(0.008)		(0.007)	(0.008)
Observations	107,304	97,292	97,292	107,304	97,292	97,292
R-squared	0.761	0.770	0.770	0.765	0.774	0.774
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Real Estate]	-0.004		0.004	-0.006		0.003
	(0.012)		(0.007)	(0.011)		(0.007)
L.Log(Rainfall)×I[Real Estate]		-0.014	-0.017*		-0.016	-0.018**
		(0.011)	(0.010)		(0.010)	(0.009)
Observations	107,387	97,372	97,372	107,387	97,372	97,372
R-squared	0.760	0.769	0.769	0.765	0.773	0.773
Year FE	NO	NO	NO	YES	YES	YES

The table depicts estimates of equation (2) using the logarithm of present and past values of rainfall as the weather measure. Dependent variable in constant COP $ (Base: Dec 2018=100). The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table A6: Effects of quarterly rainfall on commercial loan portfolio by economic sector

	Log(Gross Commercial)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log(Rainfall)×I[Health]	0.004		0.006**	0.002		0.005**
	(0.003)		(0.002)	(0.004)		(0.002)
L.Log(Rainfall)×I[Health]		0.000	-0.003		-0.002	-0.005
		(0.004)	(0.004)		(0.003)	(0.003)
Observations	107,287	97,276	97,276	107,287	97,276	97,276
R-squared	0.761	0.770	0.770	0.766	0.774	0.774
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Financial]	0.002		0.004	-0.000		0.004
	(0.007)		(0.003)	(0.006)		(0.003)
L.Log(Rainfall)×I[Financial]		-0.002	-0.004		-0.004	-0.007
		(0.008)	(0.008)		(0.008)	(0.007)
Observations	106,475	96,469	96,469	106,475	96,469	96,469
R-squared	0.757	0.766	0.766	0.762	0.770	0.770
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Manufacturing]	-0.001		0.000	-0.003		0.000
	(0.004)		(0.003)	(0.004)		(0.004)
L.Log(Rainfall)×I[Manufacturing]		-0.001	-0.001		-0.003	-0.003
		(0.005)	(0.005)		(0.005)	(0.004)
Observations	107,398	97,383	97,383	107,398	97,383	97,383
R-squared	0.760	0.769	0.769	0.764	0.772	0.772
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Transportation]	0.005		0.002	0.003		0.002
	(0.004)		(0.003)	(0.004)		(0.003)
L.Log(Rainfall)×I[Transportation]		0.008	0.007		0.005	0.004
		(0.005)	(0.005)		(0.006)	(0.006)
Observations	107,373	97,358	97,358	107,373	97,358	97,358
R-squared	0.760	0.769	0.769	0.764	0.773	0.773
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Trade]	0.002		-0.002	0.000		-0.002
	(0.003)		(0.002)	(0.003)		(0.002)
L.Log(Rainfall)×I[Trade]		0.006	0.007**		0.004	0.005
		(0.004)	(0.004)		(0.004)	(0.004)
Observations	107,398	97,383	97,383	107,398	97,383	97,383
R-squared	0.760	0.769	0.769	0.764	0.772	0.772
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[R&H]	0.006		0.002	0.005		0.002
	(0.005)		(0.004)	(0.006)		(0.004)
L.Log(Rainfall)×I[R&H]		0.007	0.006		0.006	0.005
		(0.008)	(0.007)		(0.009)	(0.007)
Observations	107,316	97,310	97,310	107,316	97,310	97,310
R-squared	0.761	0.770	0.770	0.765	0.773	0.773
Year FE	NO	NO	NO	YES	YES	YES

The table depicts estimates of equation (2) using the logarithm of present and past values of rainfall as the weather measure. Dependent variable in constant COP $ (Base: Dec 2018=100). The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table A7: Effects of rainfall shocks on commercial loan portfolio by economic sector

	Log(Gross Commercial)			
VARIABLES	(1)	(2)	(3)	(4)
RainShock[Rainfall≥80th]×I[Agriculture]	0.054***		0.009	
	(0.011)		(0.011)	
RainShock[Rainfall≤20th]×I[Agriculture]	-0.051***		-0.036***	
	(0.011)		(0.011)	
L.RainShock[Rainfall≥80th]×I[Agriculture]		0.042***		0.007
		(0.011)		(0.011)
L.RainShock[Rainfall≤20th]×I[Agriculture]		-0.068***		-0.040***
		(0.011)		(0.011)
Observations	107,239	97,235	107,239	97,235
R-squared	0.762	0.771	0.766	0.774
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Services]	0.042***		0.006	
	(0.013)		(0.013)	
RainShock[Rainfall≤20th]×I[Services]	-0.069***		-0.054***	
	(0.013)		(0.013)	
L.RainShock[Rainfall≥80th]×I[Services]		0.021		-0.015
		(0.013)		(0.013)
L.RainShock[Rainfall≤20th]×I[Services]		-0.084***		-0.055***
		(0.014)		(0.014)
Observations	107,384	97,369	107,384	97,369
R-squared	0.760	0.769	0.764	0.772
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Mining]	-0.004		-0.063***	
	(0.020)		(0.020)	
RainShock[Rainfall≤20th]×I[Mining]	0.008		0.029	
	(0.024)		(0.024)	
L.RainShock[Rainfall≥80th]×I[Mining]		0.019		-0.020
		(0.019)		(0.019)
L.RainShock[Rainfall≤20th]×I[Mining]		-0.009		0.023
		(0.021)		(0.021)
Observations	106,435	96,692	106,435	96,692
R-squared	0.758	0.768	0.763	0.772
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Electricity]	-0.021		-0.092***	
	(0.024)		(0.024)	
RainShock[Rainfall≤20th]×I[Electricity]	0.002		0.020	
	(0.028)		(0.028)	
L.RainShock[Rainfall≥80th]×I[Electricity]		0.009		-0.035
		(0.022)		(0.024)
L.RainShock[Rainfall≤20th]×I[Electricity]		-0.010		0.023
		(0.024)		(0.024)
Observations	106,515	96,509	106,515	96,509
R-squared	0.758	0.767	0.763	0.771
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Construction]	-0.008		-0.068***	
	(0.021)		(0.021)	
RainShock[Rainfall≤20th]×I[Construction]	0.017		0.036	
	(0.024)		(0.024)	
L.RainShock[Rainfall≥80th]×I[Construction]		0.011		-0.028
		(0.022)		(0.022)
L.RainShock[Rainfall≤20th]×I[Construction]		-0.009		0.025
		(0.024)		(0.024)
Observations	107,304	97,292	107,304	97,292
R-squared	0.761	0.770	0.766	0.774
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Real Estate]	0.035		-0.023	
	(0.033)		(0.033)	
RainShock[Rainfall≤20th]×I[Real Estate]	-0.031		-0.014	
	(0.036)		(0.037)	
L.RainShock[Rainfall≥80th]×I[Real Estate]		0.031		-0.007
		(0.039)		(0.039)
L.RainShock[Rainfall≤20th]×I[Real Estate]		-0.003		0.030
		(0.036)		(0.036)
Observations	107,387	97,372	107,387	97,372
R-squared	0.760	0.769	0.764	0.773
Year FE	NO	NO	YES	YES

The table depicts estimates of equation (2) using the quarterly indicators variables of rainfall above the 80th percentile and below the 20th percentile as the weather measure. Dependent variable in constant COP $ (Base: Dec 2018=100). The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table A8: Effects of rainfall shocks on commercial loan portfolio by economic sector

	Log(Gross Commercial)			
VARIABLES	(1)	(2)	(3)	(4)
RainShock[Rainfall≥80th]×I[Health]	0.050***		0.006	
	(0.016)		(0.016)	
RainShock[Rainfall≤20th]×I[Health]	-0.005		0.012	
	(0.016)		(0.016)	
L.RainShock[Rainfall≥80th]×I[Health]		0.033**		0.005
		(0.015)		(0.016)
L.RainShock[Rainfall≤20th]×I[Health]		-0.019		0.015
		(0.017)		(0.016)
Observations	107,287	97,276	107,287	97,276
R-squared	0.761	0.770	0.766	0.774
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Financial]	0.031*		0.028*	
	(0.018)		(0.017)	
RainShock[Rainfall≤20th]×I[Financial]	-0.007		0.010	
	(0.020)		(0.020)	
L.RainShock[Rainfall≥80th]×I[Financial]		0.036**		-0.000
		(0.017)		(0.017)
L.RainShock[Rainfall≤20th]×I[Financial]		-0.027		0.005
		(0.019)		(0.019)
Observations	106,475	96,469	106,475	96,469
R-squared	0.757	0.766	0.762	0.770
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Manufacturing]	0.044**		-0.010	
	(0.022)		(0.022)	
RainShock[Rainfall≤20th]×I[Manufacturing]	0.014		0.029	
	(0.020)		(0.020)	
L.RainShock[Rainfall≥80th]×I[Manufacturing]		0.038*		-0.002
		(0.022)		(0.022)
L.RainShock[Rainfall≤20th]×I[Manufacturing]		-0.002		0.031
		(0.019)		(0.019)
Observations	107,398	97,383	107,398	97,383
R-squared	0.760	0.769	0.764	0.772
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Transportation]	0.003		-0.046**	
	(0.019)		(0.019)	
RainShock[Rainfall≤20th]×I[Transportation]	0.002		0.019	
	(0.019)		(0.019)	
L.RainShock[Rainfall≥80th]×I[Transportation]		-0.009		-0.043**
		(0.017)		(0.019)
L.RainShock[Rainfall≤20th]×I[Transportation]		-0.015		0.018
		(0.020)		(0.019)
Observations	107,373	97,358	107,373	97,358
R-squared	0.760	0.769	0.764	0.773
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Trade]	0.025		-0.026	
	(0.017)		(0.017)	
RainShock[Rainfall≤20th]×I[Trade]	0.017		0.032**	
	(0.016)		(0.016)	
L.RainShock[Rainfall≥80th]×I[Trade]		0.004		-0.036**
		(0.015)		(0.016)
L.RainShock[Rainfall≤20th]×I[Trade]		-0.004		0.028*
		(0.016)		(0.016)
Observations	107,398	97,383	107,398	97,383
R-squared	0.760	0.769	0.764	0.772
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[R&H]	-0.052*		-0.104***	
	(0.028)		(0.029)	
RainShock[Rainfall≤20th]×I[R&H]	-0.027		-0.010	
	(0.025)		(0.026)	
L.RainShock[Rainfall≥80th]×I[R&H]		-0.096***		-0.134***
		(0.027)		(0.028)
L.RainShock[Rainfall≤20th]×I[R&H]		-0.010		0.023
		(0.026)		(0.027)
Observations	107,316	97,310	107,316	97,310
R-squared	0.761	0.770	0.765	0.774
Year FE	NO	NO	YES	YES

The table depicts estimates of equation (2) using the quarterly indicators variables of rainfall above the 80th percentile and below the 20th percentile as the weather measure. Dependent variable in constant COP $ (Base: Dec 2018=100). The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Appendix B: Robustness check

In Tables B1 to B4, I present the results of estimating equations 1 and 2 using a data set in which there is no imputation of the closest municipality for those banks located in municipalities for which there is no weather station information. Estimates results remain practically the same compared to the main results presented in Section 4.

Table B1: Effects of quarterly rainfall on total loans

	Log(Commercial)						Log(Consumer)						Log(Housing)						Log(Microcredit)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Log(Rainfall)	0.002		-0.001	0.003**		0.001	0.004***		0.003**	0.004***		0.003**	-0.009**		-0.009**	0.003*		0.001	0.008***		0.007***	-0.001		-0.002
	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.004)		(0.004)	(0.001)		(0.002)	(0.003)		(0.002)	(0.001)		(0.002)
L.Log(Rainfall)		0.004*	0.005**		0.004**	0.003*		0.003	0.001		0.004***	0.003*		-0.005	0.000		0.005***	0.004*		0.005***	0.001		0.003**	0.004**
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)		(0.001)	(0.002)		(0.004)	(0.003)		(0.001)	(0.002)		(0.002)	(0.001)		(0.001)	(0.002)
Observations	111,560	101,131	101,131	111,560	101,131	101,131	107,032	97,001	97,001	107,032	97,001	97,001	74,315	67,368	67,368	74,315	67,368	67,368	87,656	80,266	80,266	87,656	80,266	80,266
Municipalities	679	672	672	679	672	672	679	673	673	679	673	673	644	630	630	644	630	630	680	672	672	680	672	672
R-squared	0.756	0.765	0.765	0.760	0.768	0.768	0.843	0.847	0.847	0.846	0.850	0.850	0.798	0.805	0.805	0.811	0.816	0.817	0.738	0.744	0.744	0.755	0.756	0.756
Year FE	NO	NO	NO	YES	YES	YES	NO	NO	NO	YES	YES	YES	NO	NO	NO	YES	YES	YES	NO	NO	NO	YES	YES	YES

The table depicts estimates of equation (1) using the logarithm of present and past values of rainfall as the weather measure. Dependent variable in constant COP $ (Base: Dec 2018=100). The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table B2: Effects of rainfall shocks on total loans

	Log(Commercial)				Log(Consumer)				Log(Housing)				Log(Microcredit)			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
RainShock[Rainfall≥80th]	0.030***		-0.022**		0.069***		0.002		-0.144***		-0.009		0.059***		0.001	
	(0.010)		(0.009)		(0.012)		(0.010)		(0.016)		(0.014)		(0.012)		(0.011)	
RainShock[Rainfall≤20th]	-0.029***		-0.011		-0.003		0.010		0.057***		0.010		-0.004		0.041***	
	(0.010)		(0.010)		(0.012)		(0.012)		(0.015)		(0.015)		(0.012)		(0.011)	
L.RainShock[Rainfall≥80th]		0.024***		-0.018**		0.042***		0.001		-0.158***		-0.002		0.067***		0.007
		(0.008)		(0.008)		(0.012)		(0.010)		(0.017)		(0.014)		(0.011)		(0.010)
L.RainShock[Rainfall≤20th]		-0.053***		-0.018**		-0.022*		0.008		0.023		-0.012		-0.008		0.022**
		(0.009)		(0.009)		(0.012)		(0.011)		(0.015)		(0.015)		(0.011)		(0.011)
Observations	111,560	101,131	111,560	101,131	107,032	97,001	107,032	97,001	74,315	67,368	74,315	67,368	87,656	80,266	87,656	80,266
Municipalities	679	672	679	672	679	673	679	673	644	630	644	630	680	672	680	672
R-squared	0.756	0.765	0.760	0.768	0.843	0.847	0.846	0.850	0.798	0.806	0.811	0.816	0.738	0.744	0.755	0.756
Year FE	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES

The table depicts estimates of equation (1) using the quarterly indicators variables of rainfall above the 80th percentile and below the 20th percentile as the weather measure. Dependent variable in constant COP $ (Base: Dec 2018=100). The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table B3: Effects of quarterly rainfall on loan provisions to total loans ratio

	Commercial loan provisions						Consumer loan provisions					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(Rainfall)	0.0101		0.0097	0.0028		0.0030	0.0002***		0.0002**	-0.0001		-0.0001
	(0.0109)		(0.0097)	(0.0037)		(0.0035)	(0.0001)		(0.0001)	(0.0001)		(0.0001)
L.Log(Rainfall)		0.0129	0.0076		0.0037	0.0019		0.0005***	0.0004***		0.0001	0.0001*
		(0.0133)	(0.0082)		(0.0043)	(0.0025)		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Observations	111,521	101,093	101,093	111,521	101,093	101,093	107,002	96,975	96,975	107,002	96,975	96,975
Municipalities	679	672	672	679	672	672	679	673	673	679	673	673
R-squared	0.0089	0.0098	0.0098	0.0090	0.0099	0.0099	0.2010	0.2225	0.2225	0.2202	0.2418	0.2418
Year FE	NO	NO	NO	YES	YES	YES	NO	NO	NO	YES	YES	YES

	Housing loan provisions						Microcredit loan provisions					
VARIABLES	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Log(Rainfall)	-0.0004		-0.0004	-0.0003		-0.0000	0.0002*		0.0002**	0.0002*		0.0002
	(0.0002)		(0.0002)	(0.0002)		(0.0002)	(0.0001)		(0.0001)	(0.0001)		(0.0001)
L.Log(Rainfall)		0.0002	0.0004		0.0003	0.0003		-0.0000	-0.0002		-0.0001	-0.0002
		(0.0003)	(0.0003)		(0.0002)	(0.0002)		(0.0003)	(0.0002)		(0.0002)	(0.0002)
Observations	74,257	67,312	67,312	74,257	67,312	67,312	87,511	80,128	80,128	87,511	80,128	80,128
Municipalities	644	630	630	644	630	630	680	672	672	680	672	672
R-squared	0.4730	0.4828	0.4828	0.4795	0.4885	0.4885	0.2181	0.2242	0.2243	0.2229	0.2290	0.2290
Year FE	NO	NO	NO	YES	YES	YES	NO	NO	NO	YES	YES	YES

The table depicts estimates of equation (1) using the logarithm of present and past values of rainfall as the weather measure. The dependent variable is measured as the total loan provisions to total loans ratio. The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table B4: Effects of rainfall shocks on loan provisions to total loans ratio

	Commercial loan provisions				Consumer loan provisions				Housing loan provisions				Microcredit loan provisions			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
RainShock[Rainfall≥80th]	-0.0541		-0.0257		0.0010		0.0010*		-0.0058***		-0.0027*		0.0004		0.0010	
	(0.0456)		(0.0240)		(0.0006)		(0.0006)		(0.0016)		(0.0014)		(0.0009)		(0.0009)	
RainShock[Rainfall≤20th]	-0.0558		-0.1227		-0.0005		-0.0008		0.0000		0.0019		0.0014*		0.0004	
	(0.0841)		(0.1473)		(0.0006)		(0.0006)		(0.0015)		(0.0015)		(0.0007)		(0.0007)	
L.RainShock[Rainfall≥80th]		-0.0559		-0.0370		0.0049***		0.0002		-0.0012		0.0021		0.0006		0.0010
		(0.0509)		(0.0292)		(0.0007)		(0.0006)		(0.0016)		(0.0015)		(0.0009)		(0.0009)
L.RainShock[Rainfall≤20th]		-0.0922		-0.0977		-0.0020***		-0.0015***		-0.0021		0.0000		0.0008		-0.0001
		(0.0808)		(0.0898)		(0.0005)		(0.0005)		(0.0015)		(0.0015)		(0.0008)		(0.0008)
Observations 111,521	101,093	111,521	101,093	107,002	96,975	107,002	96,975	74,257	67,312	74,257	67,312	87,511	80,128	87,511	80,128	
Municipalities	679	672	679	672	679	673	679	673	644	630	644	630	680	672	680	672
R-squared	0.0089	0.0098	0.0090	0.0099	0.2010	0.2236	0.2202	0.2418	0.4732	0.4828	0.4796	0.4885	0.2181	0.2242	0.2229	0.2290
Year FE	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES

The table depicts estimates of equation (1) using the quarterly indicators variables of rainfall above the 80th percentile and below the 20th percentile as the weather measure. The dependent variable is measured as the total loan provisions to total loans ratio. The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Appendix C: Robustness check - Estimates by economic sectors

Table C1: Effects of quarterly rainfall on commercial loan portfolio by economic sector

	Log(Gross Commercial)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log(Rainfall)×I[Agriculture]	0.006***		0.003**	0.004**		0.003*
	(0.002)		(0.002)	(0.002)		(0.002)
L.Log(Rainfall)×I[Agriculture]		0.009***	0.008**		0.006*	0.005
		(0.003)	(0.003)		(0.004)	(0.003)
Observations	107,239	97,235	97,235	107,239	97,235	97,235
R-squared	0.761	0.771	0.771	0.766	0.774	0.774
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Services]	0.006***		0.005***	0.004		0.005**
	(0.002)		(0.002)	(0.003)		(0.002)
L.Log(Rainfall)×I[Services]		0.008***	0.005*		0.005	0.002
		(0.003)	(0.003)		(0.004)	(0.003)
Observations	107,384	97,369	97,369	107,384	97,369	97,369
R-squared	0.760	0.769	0.769	0.764	0.772	0.772
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Electricity]	-0.000		0.002	-0.002		0.001
	(0.005)		(0.003)	(0.004)		(0.003)
L.Log(Rainfall)×I[Electricity]		-0.001	-0.002		-0.004	-0.004
		(0.006)	(0.005)		(0.006)	(0.005)
Observations	106,515	96,509	96,509	106,515	96,509	96,509
R-squared	0.758	0.767	0.767	0.763	0.771	0.771
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Mining]	-0.004		-0.003	-0.006*		-0.004
	(0.004)		(0.003)	(0.004)		(0.003)
L.Log(Rainfall)×I[Mining]		-0.003	-0.000		-0.006	-0.002
		(0.006)	(0.006)		(0.006)	(0.006)
Observations	106,435	96,692	96,692	106,435	96,692	96,692
R-squared	0.759	0.768	0.768	0.763	0.772	0.772
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Construction]	-0.001		0.000	-0.003		-0.000
	(0.005)		(0.002)	(0.005)		(0.003)
L.Log(Rainfall)×I[Construction]		-0.002	-0.002		-0.005	-0.004
		(0.007)	(0.006)		(0.006)	(0.006)
Observations	107,304	97,292	97,292	107,304	97,292	97,292
R-squared	0.761	0.770	0.770	0.765	0.774	0.774
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Real Estate]	-0.003		-0.000	-0.005		-0.001
	(0.008)		(0.004)	(0.007)		(0.004)
L.Log(Rainfall)×I[Real Estate]		-0.008	-0.007		-0.010	-0.009
		(0.009)	(0.008)		(0.008)	(0.007)
Observations	107,387	97,372	97,372	107,387	97,372	97,372
R-squared	0.760	0.769	0.769	0.765	0.773	0.773
Year FE	NO	NO	NO	YES	YES	YES

The table depicts estimates of equation (2) using the logarithm of present and past values of rainfall as the weather measure. Dependent variable in constant COP $ (Base: Dec 2018=100). The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table C2: Effects of quarterly rainfall on commercial loan portfolio by economic sector

	Log(Gross Commercial)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log(Rainfall)×I[Health]	0.004		0.006**	0.002		0.005**
	(0.003)		(0.002)	(0.003)		(0.003)
L.Log(Rainfall)×I[Health]		0.000	-0.003		-0.002	-0.005
		(0.004)	(0.004)		(0.003)	(0.003)
Observations	107,287	97,276	97,276	107,287	97,276	97,276
R-squared	0.761	0.770	0.770	0.766	0.774	0.774
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Financial]	0.003		0.004	0.000		0.004
	(0.006)		(0.003)	(0.006)		(0.003)
L.Log(Rainfall)×I[Financial]		-0.001	-0.003		-0.003	-0.005
		(0.008)	(0.007)		(0.007)	(0.007)
Observations	106,475	96,469	96,469	106,475	96,469	96,469
R-squared	0.757	0.766	0.766	0.762	0.770	0.770
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Manufacturing]	-0.001		0.000	-0.003		0.000
	(0.004)		(0.003)	(0.004)		(0.004)
L.Log(Rainfall)×I[Manufacturing]		-0.001	-0.001		-0.003	-0.003
		(0.005)	(0.005)		(0.005)	(0.004)
Observations	107,398	97,383	97,383	107,398	97,383	97,383
R-squared	0.760	0.769	0.769	0.764	0.772	0.772
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Transportation]	0.005		0.002	0.003		0.001
	(0.003)		(0.003)	(0.003)		(0.003)
L.Log(Rainfall)×I[Transportation]		0.007*	0.006*		0.005	0.004
		(0.004)	(0.004)		(0.005)	(0.004)
Observations	107,373	97,358	97,358	107,373	97,358	97,358
R-squared	0.760	0.769	0.769	0.764	0.773	0.773
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[Trade]	0.003		-0.002	0.002		-0.002
	(0.003)		(0.003)	(0.004)		(0.002)
L.Log(Rainfall)×I[Trade]		0.007*	0.009**		0.005	0.007*
		(0.004)	(0.003)		(0.004)	(0.004)
Observations	107,398	97,383	97,383	107,398	97,383	97,383
R-squared	0.760	0.769	0.769	0.764	0.772	0.772
Year FE	NO	NO	NO	YES	YES	YES
Log(Rainfall)×I[R&H] 0.000		-0.001	-0.001		-0.002	
	(0.003)		(0.002)	(0.003)		(0.002)
L.Log(Rainfall)×I[R&H]		-0.000	0.001		-0.002	-0.001
		(0.004)	(0.004)		(0.004)	(0.004)
Observations	107,316	97,310	97,310	107,316	97,310	97,310
R-squared	0.761	0.770	0.770	0.765	0.773	0.773
Year FE	NO	NO	NO	YES	YES	YES

The table depicts estimates of equation (2) using the logarithm of present and past values of rainfall as the weather measure. Dependent variable in constant COP $ (Base: Dec 2018=100). The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table C3: Effects of quarterly rainfall on commercial loan portfolio by economic sector

	Log(Gross Commercial)			
VARIABLES	(1)	(2)	(3)	(4)
RainShock[Rainfall≥80th]×I[Agriculture]	0.031***		0.018	
	(0.011)		(0.011)	
RainShock[Rainfall≤20th]×I[Agriculture]	-0.036***		-0.021**	
	(0.010)		(0.010)	
L.RainShock[Rainfall≥80th]×I[Agriculture]		0.013		0.025**
		(0.011)		(0.011)
L.RainShock[Rainfall≤20th]×I[Agriculture]		-0.055***		-0.026**
		(0.011)		(0.011)
Observations	107,239	97,235	107,239	97,235
R-squared	0.762	0.771	0.766	0.774
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Services]	0.044***		-0.004	
	(0.011)		(0.012)	
RainShock[Rainfall≤20th]×I[Services]	-0.040***		-0.024*	
	(0.012)		(0.012)	
L.RainShock[Rainfall≥80th]×I[Services]		0.033***		-0.002
		(0.011)		(0.012)
L.RainShock[Rainfall≤20th]×I[Services]		-0.063***		-0.035***
		(0.012)		(0.012)
Observations	107,384	97,369	107,384	97,369
R-squared	0.760	0.769	0.764	0.772
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Mining]	0.000		-0.055**	
	(0.024)		(0.025)	
RainShock[Rainfall≤20th]×I[Mining]	0.025		0.045*	
	(0.023)		(0.024)	
L.RainShock[Rainfall≥80th]×I[EMining]		0.020		-0.021
		(0.024)		(0.026)
L.RainShock[Rainfall≤20th]×I[Mining]		0.025		0.059**
		(0.025)		(0.025)
Observations	106,435	96,692	106,435	96,692
R-squared	0.758	0.768	0.763	0.772
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Electricity]	-0.030		-0.102***	
	(0.022)		(0.022)	
RainShock[Rainfall≤20th]×I[Electricity]	-0.002		0.016	
	(0.025)		(0.025)	
L.RainShock[Rainfall≥80th]×I[Electricity]		0.005		-0.040*
		(0.021)		(0.022)
L.RainShock[Rainfall≤20th]×I[Electricity]		-0.013		0.021
		(0.022)		(0.021)
Observations	106,515	96,509	106,515	96,509
R-squared	0.758	0.767	0.763	0.771
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Construction]	0.019		-0.037**	
	(0.017)		(0.016)	
RainShock[Rainfall≤20th]×I[Construction]	0.015		0.033*	
	(0.019)		(0.019)	
L.RainShock[Rainfall≥80th]×I[Construction]		0.021		-0.019
		(0.017)		(0.017)
L.RainShock[Rainfall≤20th]×I[Construction]		-0.010		0.024
		(0.019)		(0.019)
Observations	107,304	97,292	107,304	97,292
R-squared	0.761	0.770	0.766	0.774
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Real Estate]	0.039*		-0.019	
	(0.021)		(0.021)	
RainShock[Rainfall≤20th]×I[Real Estate]	0.011		0.027	
	(0.022)		(0.022)	
L.RainShock[Rainfall≥80th]×I[Real Estate]		0.026		-0.015
		(0.025)		(0.025)
L.RainShock[Rainfall≤20th]×I[Real Estate]		0.009		0.042*
		(0.024)		(0.024)
Observations	107,387	97,372	107,387	97,372
R-squared	0.760	0.769	0.764	0.773
Year FE	NO	NO	YES	YES

The table depicts estimates of equation (2) using the quarterly indicators variables of rainfall above the 80th percentile and below the 20th percentile as the weather measure. The indicator variable of bank exposure is calculated using the median share. Dependent variable in constant COP $ (Base: Dec 2018=100). The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.

Table C4: Effects of quarterly rainfall on commercial loan portfolio by economic sector

	Log(Gross Commercial)			
VARIABLES	(1)	(2)	(3)	(4)
RainShock[Rainfall≥80th]×I[Health]	0.050***		0.006	
	(0.016)		(0.016)	
RainShock[Rainfall≤20th]×I[Health]	-0.005		0.012	
	(0.016)		(0.016)	
L.RainShock[Rainfall≥80th]×I[Health]		0.033**		0.005
		(0.015)		(0.016)
L.RainShock[Rainfall≤20th]×I[Health]		-0.019		0.015
		(0.017)		(0.016)
Observations	107,287	97,276	107,287	97,276
R-squared	0.761	0.770	0.766	0.774
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Financial]	0.027		-0.031*	
	(0.017)		(0.016)	
RainShock[Rainfall≤20th]×I[Financial]	-0.004		0.014	
	(0.019)		(0.019)	
L.RainShock[Rainfall≥80th]×I[Financial]		0.030*		-0.007
		(0.017)		(0.017)
L.RainShock[Rainfall≤20th]×I[Financial]		-0.025		0.008
		(0.019)		(0.019)
Observations	106,475	96,469	106,475	96,469
R-squared	0.757	0.766	0.762	0.770
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Manufacturing]	0.044**		-0.010	
	(0.022)		(0.022)	
RainShock[Rainfall≤20th]×I[Manufacturing]	0.014		0.029	
	(0.020)		(0.020)	
L.RainShock[Rainfall≥80th]×I[Manufacturing]		0.038*		-0.002
		(0.022)		(0.022)
L.RainShock[Rainfall≤20th]×I[Manufacturing]		-0.002		0.031
		(0.019)		(0.019)
Observations	107,398	97,383	107,398	97,383
R-squared	0.760	0.769	0.764	0.772
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Transportation]	0.001		-0.051***	
	(0.018)		(0.019)	
RainShock[Rainfall≤20th]×I[Transportation]	0.010		0.027	
	(0.019)		(0.019)	
L.RainShock[Rainfall≥80th]×I[Transportation]		-0.020		-0.057***
		(0.017)		(0.018)
L.RainShock[Rainfall≤20th]×I[Transportation]		-0.009		0.025
		(0.020)		(0.020)
Observations	107,373	97,358	107,373	97,358
R-squared	0.760	0.769	0.764	0.773
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[Trade]	0.015		-0.033*	
	(0.020)		(0.019)	
RainShock[Rainfall≤20th]×I[Trade]	0.002		0.016	
	(0.018)		(0.018)	
L.RainShock[Rainfall≥80th]×I[Trade]		-0.011		-0.049**
		(0.018)		(0.019)
L.RainShock[Rainfall≤20th]×I[Trade]		-0.014		0.017
		(0.019)		(0.019)
Observations	107,398	97,383	107,398	97,383
R-squared	0.760	0.769	0.764	0.772
Year FE	NO	NO	YES	YES
RainShock[Rainfall≥80th]×I[R&H]	0.002		-0.054***	
	(0.014)		(0.014)	
RainShock[Rainfall≤20th]×I[R&H]	0.011		0.029**	
	(0.014)		(0.015)	
L.RainShock[Rainfall≥80th]×I[R&H]		-0.019		-0.060***
		(0.015)		(0.015)
L.RainShock[Rainfall≤20th]×I[R&H]		0.005		0.039***
		(0.015)		(0.015)
Observations	107,316	97,310	107,316	97,310
R-squared	0.761	0.770	0.765	0.774
Year FE	NO	NO	YES	YES

The table depicts estimates of equation (2) using the quarterly indicators variables of rainfall above the 80th percentile and below the 20th percentile as the weather measure. The indicator variable of bank exposure is calculated using the median share. Dependent variable in constant COP $ (Base: Dec 2018=100). The regressions that do not include year fixed effects include an annual linear trend. Municipal-level, bank-level and quarter-level fixed effects included in all columns. Municipality-level clustered robust standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level respectively.