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PATRÍCIA AMADI OLIVEIRA

DROUGHT SHOCK, STATE-OWNED BANK AND LOCAL ECONOMIC PERFORMANCE

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Dissertação apresentada à Escola de Economia de São Paulo como pré-requisito à obtenção de título de mestre em Economia de Empresas.

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Resumo

Esta dissertação estuda como os choques de seca afetam os bancos públicos e o desenvolvimento econômico local usando os dados brasileiros. Primeiramente, estudamos os efeitos dos choques de seca sobre o crédito público, as taxas de inadimplência e as medidas de desempenho econômico local nos municípios do semiárido brasileiro. Nossa estratégia de identificação explora a variação nos históricos de precipitação para comparar municípios com características semelhantes, mas que foram atingidos por níveis diferentes de seca. Os resultados mostram que os locais mais expostos à seca apresentaram queda do crédito e do PIB, enquanto os índices de inadimplência aumentaram, apesar disso, não foram identificados efeitos para o setor formal. Em seguida, investigamos os impactos do crédito público abundante comparando municípios vizinhos que operam sob diferentes regimes de crédito, mas que foram igualmente expostos à seca. Encontramos um efeito negativo no PIB local, mesmo com efeitos positivos no crédito público durante o choque da seca nas áreas elegíveis para crédito subsidiado. O tema tem implicações importantes para as políticas públicas voltadas para o desenvolvimento, porque o crédito patrocinado pelo governo pode ser uma estratégia de enfrentamento a choques climáticos adversos, especialmente para as áreas de baixa renda.

Palavras-chaves: Choques de seca, Crédito Público, Economias Locais, Clima, Desenvolvimento.

Abstract

This thesis studies how drought shocks affect public banks and local economic development using Brazilian data. First, we study the effects of drought shocks on public credit, delinquency rates, and measures of local economic performance in Brazil's Semiarid municipalities. Our identification strategy exploits variation in rainfall records to compare municipalities with similar characteristics but were hit by different levels to the drought. The results show that localities more exposed to the drought presented a decrease in credit, and GDP, while the delinquency rates increased. Despite this, no effects for the formal sector were identified. We then investigate the impacts of abundant public credit comparing neighboring municipalities that operate under different credit regimes but were equally exposed to the drought. We find a negative effect on local GDP, even with positive effects in public credit during the drought shock in those areas eligible for subsidized credit. The topic has important implications for development-oriented public policy because government-sponsored credit may be a coping strategy to adverse weather shocks, especially for the low-income areas.

Keywords: Drought Shock, Public Credit, Local Economies, Climate, Development.

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Lista de abreviaturas e siglas

BNB	Banco do Nordeste do Brasil
DS	Drought Shock
ESTBAN	Estatísticas Bancárias
FCO	Fundo Constitucional de Financiamento do Centro-Oeste
FNE	Fundo Constitucional de Financiamento do Nordeste
FNO	Fundo Constitucional de Financiamento do Norte
GDP	Gross Domestic Product
IBGE	Instituto Brasileiro de Geografia e Estatistica
IDB	Inter-American Development Bank
INMET	Instituto Nacional de Meteorologia
PNDR	Política Nacional de Desenvolvimento Regional
PRONAF	Programa Nacional de Fortalecimento da Agricultura Familiar
RAIS	Relação Anual de Informações Sociais

Sumário

1 Introduction

Climate Change may affect the likelihood of extreme weather events become more frequent and intense in the coming decades (IPCC, 2014). The changes in climate patterns and warmer temperatures have severe consequences for agriculture, especially for regions highly dependent on agriculture, which is the case of several developing countries (YOHE et al., 2007). Therefore, understanding the potential impacts of these shocks is fundamental for policy formulation to support these areas during these extreme weather events. There is a lack of studies investigating the distributional impacts of weather shocks, especially for poor countries. The evaluation of this shock is concentrated only in analysis through aggregate measures such as the Gross Domestic Product, which may hide the impacts on more vulnerable people or regions (HALLEGATTE; ROZENBERG, 2017; WINSEMIUS et al., 2018).

In this thesis, we evaluate the impact of a severe drought on economic performance, credit, and delinquency rates by public bank in low-income and climate-vulnerable areas. To the best of our knowledge, this is the first study to show how a state-owned bank reacts to drought shocks. The assessment is particularly important because the region affected is highly dependent on government-sponsored credit and also for the reason that the credit may have a fundamental role in support these areas during extreme weather events.

This study analyzes the effect of a drought shock that happened in the Brazilian Northeast from 2012 to 2017. The drought was the most severe recorded in history for the region - in this period the average precipitation was below of historical average in all years for all municipalities. We concentrate the analysis on the semiarid region, Brazil´s poorest region, and also an area subject to reoccurring drought. Furthermore, this region is the most populous semiarid region in the world (AB'SÁBER, 1999) and the largest concentration of rural population in Brazil. Therefore, evaluating the impact on these local economies could be a good instrument to understand which sectors are most affected and also for policy formulation of the mitigation in low-income regions.

The analysis is organized into two parts. In the first, we use a differences-indifferences strategy for analyzing the impact of drought on the local economic variables. We compare (before and after) the performance of areas with different intensities of drought shocks but with similar characteristics in socioeconomics and geography. The identification assumption is that hardest-hit municipalities would have had a similar trend in the outcomes as those where the drought-hit is less strong, in the absence of the drought.

The results of the first part of the thesis show that the drought shock had negative effects on the Gross Domestic Product but did not significantly affect the employment of formal firms. Additional analysis suggests that the most affected by drought are the informal sector. This result is particularly important for policy formulation, it may indicate that the formal sector presumably already has actions in mitigating the negative impact caused by extreme weather events, such as insurance, or better technologies. In addition, the government bank has reduced credit in areas highly affected by drought, this aspect is particularly relevant because the credit supply may have an important role in coping with the negative weather shocks, especially in low-income areas that often exhibit constraints credit.

In the second part of the study, we evaluate if the availability of public credit supply is determinant to economic performance during the drought shocks. We analyze areas with a similar level of drought shocks and demand for credit but with different patterns of credit supply. The most important regional development fund of Brazil, FNE (Fundo Constitucional de Financiamento do Nordeste), allocates at least 50% of its subsidized credit for producers located in the semiarid region - this causes that the credit regime is more favorable to municipalities in semiarid. In our empirical strategy, we compare the performance of neighbor municipalities, where some areas are into the semiarid delimitation, and others are outside. Our identification is that bordering municipalities may have similar observable and unobservable characteristics, and the same intensity of drought, but they were not included in semiarid and consequently receive less credit by only institutional criteria. The findings pointed out that the more availability of credit did not influence the results on local economic performance during the drought shock.

The findings in this study contribute to several strands of the economics literature. First, they contribute to research that studies the effects of weather shocks on economic performance - the differential of our work is that we analyze the impact of a severe and persistent drought for local economies in low-income areas. There is a lack of studies investigating the distributional impacts of droughts within countries or the impact on more vulnerable people. A set of research evaluates the impact of weather shocks at the country level considering only macroeconomics effect, although these analyses are also very important, they can hide the real impact of these events. The evaluation only based on the aggregate effect is not enough for the complete understanding of which sectors, firms - and people are most affected.

The second contribution is that the setting allows analyzing the impact of a prolonged, unexpected, and severe drought shock. This setting is particularly relevant for the reason that droughts are widespread for the whole world (DILLEY et al., 2005), with major negative impacts for poor countries that have particular constraints of data and analysis. Furthermore, the duration has the most important role in characterizing a drought (PELLING et al., 2004). As the weather events are becoming more frequent and more intense to deliver more resilient economies and greater social inclusion, we must know the consequences of these events.

Third, the thesis is (to the best of my knowledge) the first to show how the public credit market reacts to drought shock. The financial market has several impacts on development, then shifts in this structure may have crucial effects on the economic development of vulnerable areas. Moreover, we study the impact of public credit as a coping strategy of drought for local economies. This analysis is relevant especially with the increase in extreme weather events and the changes in climate risk. Guaranteeing an accurate investigation demands rich local-level data that allow following the loan levels over the time in each locality and our data allow identify loan at municipality-level. Furthermore, to study the effects and mitigate endogeneity concerns, we need to rely on a plausibly exogenous and well-defined variation on credit supply. Thus, we choose to study the municipality of the Brazilian northeast to overcome these obstacles.

This thesis proceeds as follows. Chapter 2 presents the literature review. Chapter 3 provides the background on the Brazilian Semiarid Region, detail about the drought shock, the acting of the Bank of Northeast, and the Northeast Constitutional Fund. We describe the data in Chapter 4. Chapter 5 shows the empirical strategy and the discussion about the threats to the identification. Chapter 6 presents the results. Chapter 7 concludes.

2 Literature

Extreme weather events may be defined as rare and severe climate events causing a lot of capital destructions over time, such as hurricanes, floods, droughts, heatwaves, cold waves, and storms. Climate projections tell us that changing climate patterns are likely to increase the frequency and magnitude of these events (IPCC, 2014). In the last decades, the number of extreme weather events had a large increase, where the global loss associated with the occurrences of these events in 2019 caused about $ 150 billion, besides thousands of deaths (LOW, 2020). However, the literature has been shown that the analysis of the effects is complex (LOAYZA et al., 2009; NOY, 2009), because the results vary according to the context related to each event. To better understanding the impacts, it is necessary a thorough analysis, as an evaluation split by sector of economic activity, by category of weather events, and by the intensity of the shock (FOMBY; IKEDA; LOAYZA, 2013).

Most of the papers in climate literature provide empirical analysis exploring the impact of historical weather fluctuations on economic activity (DELL; JONES; OLKEN, 2012). The weather variability can influence economic activity through various channels as agricultural output (SCHLENKER; LOBELL, 2010; DESCHÊNES; GREENSTONE, 2007; LOBELL; SCHLENKER; COSTA-ROBERTS, 2011; BURKE; EMERICK, 2016; ARAGÓN; OTEIZA; RUD., 2021), industrial output (JONES; OLKEN, 2010; DELL; JONES; OLKEN, 2012), labor productivity (GRAFF; NEIDELL, 2014), human capital (GRAFF; NEIDELL, 2014), health (HAJAT et al., 2005; DESCHÊNES; MORETTI, 2009; DESCHÊNES; GREENSTONE, 2011; ROCHA; SOARES., 2015), conflict (HIDALGO et al., 2010; BURKE; LEIGH, 2010; BRUCKNER; CICCONE, 2011; DELL, 2012; HSIANG; BURKE; MIGUEL, 2019; HARARI; FERRARA, 2018), and others (DELL; JONES; OLKEN, 2014).

The findings in this thesis contribute to the literature on the evaluation of weather shock on local economic activity. In this study, we analyzed the impact of a prolonged, unexpected, and severe drought for low-income localities. We focus on drought shock because the drought has a large negative impact on economic activity (RADDATZ, 2009). Furthermore, droughts are not localized in specific regions and may occur in the whole world impacting several regions. Unlike other extreme weather events, such as floods and hurricanes that result in a large loss in a short period, the drought has a slow pace and visible results only after a long period of low rainfall, which may hamper the evaluation of the economic impacts.

Another concern about the impact of the drought is the relevance for the agriculture sector and consequently, the impact on economies highly dependent on agriculture, given that temperature and precipitation are direct inputs of the sector. Studies have shown that drought has negative effects on the agriculture sector (LI et al., 2009; COREY; ROWHANI; RAMANKUTTY, 2016; HONG; WEIKA; XU, 2019; DO et al., 2020). This is a trend especially threatened for low-income developing countries that tend to be more exposed and vulnerable to the weather variability and dependent on agriculture for their livelihoods.

The analysis of how weather fluctuation affects economic activity have gained attention in the literature, but this analysis typically considers only its impact on macroe-

conomic aggregates. There is a lack of literature on investigating the distributional impacts of droughts within countries or the impact for poor people, results that may do not be capture for national income (HALLEGATTE; ROZENBERG, 2017; WINSEMIUS et al., 2018). In this thesis, we document the effects of drought on local economic performance for municipalities in low-income areas.

An important question, especially for low-income countries, is the coping strategies with weather shocks. There is a broad range of coping strategies, like migration, infrastructure investment, financial sector policies, labor market policies, health policies, well-target social safety nets, fiscal incentives, and the development of appropriate technologies (ACEVEDO et al., 2020). The thesis concentrated on understanding of distributional consequences of weather variability and the role of the credit market as a coping strategy, because households in low-income developing countries, which tend to have limited access to savings and credit, appear to be more harmed by weather-induced income shocks (IMF, 2016).

Furthermore, we concentrated the analysis on credit provided by state-owned banks, the literature finds that government banks are often used as an instrument of political interests instead of development aims, and are correlated with weak financial development and institutions (PORTA; LOPEZ-DE-SILANES; SHLEIFER, 2002; SAPIENZA., 2004; CARVALHO, 2014). However, the public bank might provide counter-cyclical support that tends to be less responsive to macroeconomic shocks than private banks (CULL; MARTINEZ-PERIA, 2013; COLEMAN; FELER, 2015). However, there is a gap in the literature on the role of banking ownership and government-sponsored credit for local economies in poor and climate-vulnerable areas (MATA; RESENDE, 2020), mostly in a future with rises extreme weather events, that will become this set of economies riskier, the public credit supply may have a fundamental role to assist areas during weather shocks.

3 Background

1 Brazilian Semiarid Region

The Brazilian Semiarid region is the least developed region of the country and is geographically vulnerable to water scarcity. The region is delimited by the federal government, considering the weather conditions that prevail in the semiarid contexts, mainly precipitation. [1] The hydrography is subject to recurrent episodes of water deficit since most rivers are non-perennial — one notable exception being the São Francisco river.

The delimitation of the (municipalities belonging to) semiarid changed in 2005 and 2017. For this thesis, we use the delimitation that prevailed between 2005 and 2017. According to data from the last Brazil Demographic Census (2010), the population of the semiarid region exceeded 22 million inhabitants, which represented almost 12% of the entire Brazilian population. There were 1,135 municipalities spread over Northeast and the Southeast, occupying the states of Maranhão, Piauí, Ceará, Rio Grande do Norte, Paraíba, Pernambuco, Alagoas, Sergipe, Bahia, and Minas Gerais. In figure 1, we can see the spatial distribution of semiarid municipalities on Brazil territory, considering the delimitation in 2011.

Brazilian Semiarid's area added up to 982,563.3 km² in which the Northeast Region concentrated nearly 89.5% of this territory. The region is the largest concentration of rural population in the country and it is the most populous semiarid region in the world (AB'SÁBER, 1999), but compared to other semi-arid regions in the world, where it rains between 80 to 250mm per year, the Brazilian semiarid region is the rainiest in the planet (averaging 200 to 800mm annually).

The main economic sector is agriculture and livestock, involving more than 1.7 million farmers and livestock producers (MATA; RESENDE, 2020). The Semiarid has high level of land and water concentration (SILVA et al., 2010), moreover, the major biome, the Caatinga, had in last years a lot of environmental degradation from 2001 to 2018 - the deforestation was 60.769,39 km² (SANTOS; NASCIMENTO; SILVA, 2020). These features added with its geographical characteristics become the region more susceptible to land degradation, an aspect that may be more relevant for small farmers because many of them do not have access to better inputs of production and depend on natural resources.

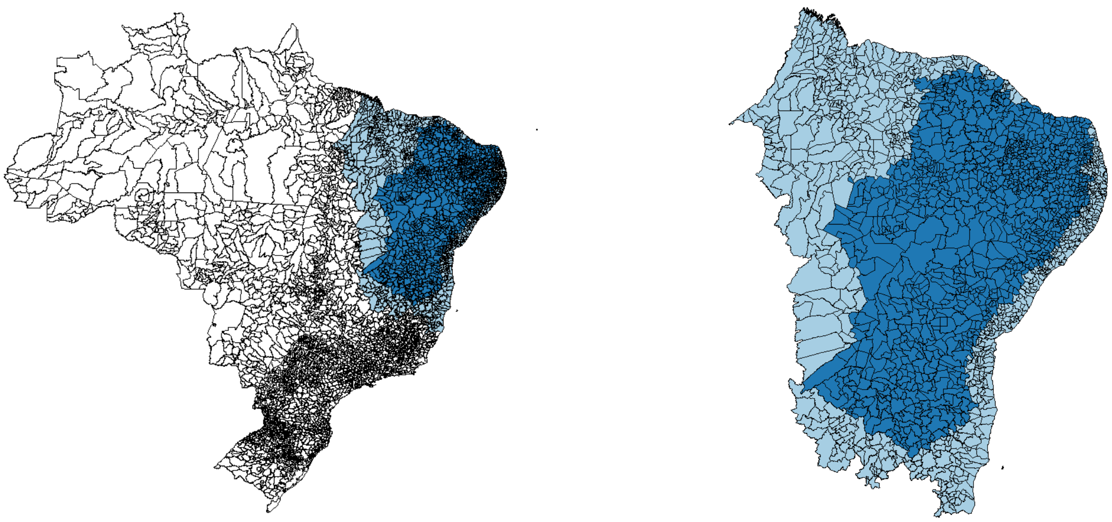
Given its geographical, climate, economic, and social characteristics, aforementioned, extreme weather events may have a determinant effect in this region, which already has persistent developmental challenges.

1.1 Banking in the Semiarid.

According to data from Estatística Bancária (ESTBAN), the semiarid banking industry is highly concentrated: in 2011, there were 1386 bank branches, but only six main banks dominated the market. In particular, the market has a high share of a public bank,

[1] The criteria used to delimit the Semiarid were average annual rainfall equal to or lower than 800 mm; Aridity Index equal to or lower than 0.50; and daily percentage of water deficit equal to or greater than 60%, considering all the days in the year. (Source: <https://www.ibge.gov.br/geociencias/cartas-e-mapas/mapas-regionais/15974-semiarido-brasileiro.html?=&t=sobre>)

Figure 1 – Maps of Semiarid Brazil



(a) Brazil Area

(b) Sudene Area

Notes: Maps of Semiarid Brazilian divided into today's municipalities. The figure shows the classification before the drought. The municipalities inside the semiarid are dark blue (a total of 1135), and the municipalities outside but in Sudene's area are light blue. Item (a) show all Brazilian municipalities. Item (b) shows only Sudene's area.

but a low banking presence, about 50% of municipalities do not have any bank branches. For these, 40% have government banks share equal to or above 0.5. Even if there is no bank branch in the municipality, a borrower can obtain a loan from a bank branch located in a neighboring municipality, but for small producers, farther bank branches may be an important constraint. This aspect evidences the importance of public banks for the semiarid region.

2 The Drought of 2012-2017

The droughts affect various parts of the world on different continents and countries. In Brazil, its occurrence is directly related to phenomena such as El Niño and La Niña that alter the rainfall regime of these regions. The Northeast region of Brazil has historically always suffered from drought, particularly the semiarid. The severe dry periods have been reports since the time of Portuguese colonization (LIMA; MAGALHÃES, 2018).

The drought of 2012-2017 that hit the Brazilian Semiarid was the most prolonged drought recorded for the region (INMET). [2] Since that started the tracking in 1845 there had never been six consecutive years with below-average rainfall.

According to data from *Secretaria Nacional de Defesa Civil*, almost every municipality in every state in the Northeast region was affected somehow by the drought. The following table 1 shows quantitatively the emergency in each state according to data *Defesa Civil*. In the first year of drought (2012), the number of municipalities that declared an emergency in the area of operation of the Sudene, increased about 1,500% compared to

[2] Instituto Nacional de Meteorologia (INMET) is the meteorological institute of Brazil. It is part of the Ministry of Agriculture, Livestock, and Food Supply of Brazil.

2011. Most of them are in the states of Bahia, Piauí, and Paraíba. However, the level of municipalities in this situation keep high until the last years of the drought period. Once the emergency has been decreed, additional support resources may be requested from the Federal Government for operations as *"Carro-Pipa"* to supporting the supply of drinking water to areas affected by drought. [3]

Even if the Semiarid already faced dry season in other years, the 2012–2017 drought was an unexpected and extreme weather event for the reason of time extension of the event. The impacts of prolonged droughts not harming only human use, but also productive activities (MATA; FREITAS; RESENDE, 2019), demanding specific coping strategies for the region such as credit policies (FREITAS, 2019).

Table 1 – Total of municipalities declared a State of Emergency from 2011 to 2017

Sudene's States	2011	2012	2013	2014	2015	2016	2017
Alagoas	0	36	59	43	38	40	71
Bahia	40	263	227	171	133	79	224
Ceará	7	177	177	176	139	127	94
Espírito Santo	1	1	3	3	16	13	3
Maranhão	0	73	75	11	2	11	0
Minas Gerais	10	122	139	147	94	80	65
Paraíba	11	196	202	198	197	196	197
Pernambuco	11	121	130	125	126	125	71
Piauí	4	194	211	204	209	122	42
Rio Grande do Norte	0	142	161	160	153	153	153
Sergipe	5	18	39	17	8	16	27
Total of Municipalities	89	1.343	1.423	1.255	1.115	962	947

Notes: The table taken from Santana e Santos (2020) show the number of municipalities that declared an emergency situation in each state between the years of 2011 to 2017.

3 Bank of Northeast and the Northeast Constitutional Fund

Bank of Northeast (BNB) is a Brazilian regional financial institution with features of commercial and development banks. Its headquarters is located in Fortaleza, Ceará. The bank was founded in 1952, currently, through its 300 bank branches, the bank is present in all states of the Northeast region of Brazil, and also in the states of Minas Gerais and Espírito Santo.

[3] See for more details <http://www.defesacivil.ce.gov.br/index.php?option=com_content&view=article&id=651&Itemid=192>

The bank is a financial institution organized under the form of a mixed economy company, publicly listed, with over 90% of its capital under the control of the Federal Government. The bank is the largest institution in Latin America focused on regional development, its principal purpose is promoting the development of the SUDENE [4] area through financial support to producers of the region. BNB operates several public policies, with the operationalization of programs such as the National Program for the Strengthening of Family Farming (PRONAF) and the administration of the Constitutional Fund for Financing in the Northeast (FNE), the main source of operational funds for the company (more details below). In addition to federal resources, the Bank has access to other sources of financing in the domestic and foreign markets, through partnerships and alliances with national and international institutions, including multilateral institutions, such as the World Bank and the Inter-American Development Bank (IDB). [5] Bank of Northeast promoted 4.9 million credit operations in 2017, amounting to R$ 26.4 billion - of this amount, R$ 15.97 billion stems from *Fundo Constitucional de Financiamento do Nordeste* (FNE).

3.1 The Northeast Constitutional Fund (FNE).

The Constitutional Financing Funds ("*Fundos Constitucionais de Financiamento*") respectively, for the Northeast, FNE, the Center-West, FCO, and the North, FNO, were created by the 1988 Federal Constitution of Brazil to provide subsidized loans to promote the economic and social development of these Brazilian regions. These funds are financed by a percentage of income taxes and by the tax on industrialized goods, 3% in both cases. Of the total resources, 60% goes to the FNE, and the rest is equally divided between the FCO and the FNO. These resources are operated by regional banks, which are the Banco do Nordeste (FNE), Banco da Amazônia (FNO) and Banco do Brasil (FCO). Thus, FNE is the main Regional Policy in Brazil and BNB is responsible for managing the loans from the resources of the fund.

The BNB bank lends with below-market interest rates to producers of the region, with priority to small rural producers, micro and small enterprises, to the semiarid region and the municipalities hosted in micro-regions and typologies of municipalities defined by the National Policy for Regional Development (PNDR).[6] The bank has a variety of products that could have a schedule of payments, collateral, and late fees for delayed payments depending on the design of the loan.

In 2017, BNB was responsible for the managed amount of R $ 12.3 billion, distributed in more than 582 thousand credit operations, covering all 1,990 municipalities in FNE's area of operation, financing rural and urban developments of all sizes, from family farmers and individual microentrepreneurs, medium and large industrial and infrastructure (BNB, 2017).

In sum, BNB bank can provide subsidized credit to producers in the Sudene area (semiarid and non-semiarid). However, there are differences in the credit regime between the regions. First, at least half of the FNE's resources are driven for the semiarid region.

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4 SUDENE's area of activity fully covers the States of Maranhão, Piauí, Ceará, Rio Grande do Norte, Paraíba, Pernambuco, Alagoas, Sergipe, Bahia and, partially, the States of Minas Gerais and Espírito Santo.

5 See *Portal do Banco do Nordeste do Brasil*: https://www.bnb.gov.br/historico

6 This Policy split all Brazilian municipalities into four typologies of development to determine which are priorities to regional development policies

In addition, there is a 15% “bonus” on interest paid up to the due date. If the project is located in municipalities in the semiarid region of the Northeast, the benefit for payment on time rises to 25%. In addition, the financing term given by the fund is up to 12 years, including up to a 4-year grace period. For municipalities located in the semiarid region, the term is up to 15 years, including a grace period of up to 5 years (CNI, 2011). Thus, the borrowers in the semiarid region have a more favorable credit supply. Although, in 2013, the bonus differential was repealed by Federal Law n. 12,793, and producers inside and outside the semiarid were eligible to the same bonus of 15% (BNB, 2013).

4 Data

The spatial unit of analysis is the municipality. Our data span from 2006 to 2017, so we can use pre, and post-drought information. The reason for the choice of this range of time is just to analyze six years before the start of the drought, and the six years after. We use five sources of data in this study: BNB's administrative data, IBGE, RAIS, and *Terrestrial Air Temperature and Precipitation: 1900–2017 Gridded Monthly Time Series.*

The BNB's administrative dataset has rich information from 2006 to 2017 of the credit market because this data set has the exact information of what municipality receives the loans provided by the BNB Bank - the data is not aggregate in the municipality of the bank branch in which the credit was requested, that is, we know in which municipality the loans are used. Additionally, the information is split into owned resources of BNB bank and FNE. The dataset has information on the value loans, the number of operations, the number of default loans, and the sectoral activity of the loan. We aggregate the information to provide municipal-level data.

The municipality's characteristics, including population, rural population, income, years of schooling, illiteracy rate, Gini index, poverty rate, percentage of the house with water, and percentage of the houses with electricity are collected from the Brazil Demographic Census 2010 provided by the Brazilian Bureau of Statistics (IBGE). Additionally, we used the yearly IBGE's Gross, Domestic Product (GDP) data on municipal GDP and sector GDP.

Our basic source for formal market outcomes in Brazilian Northeast is from the Relação Anual de Informações Sociais (RAIS), an annual dataset that is relevant for the country and municipality. It contains detailed information on all formal-sector employees and firms. In this thesis, we use the information at the municipality level of the total jobs.

We construct historical series of temperature and precipitation using, respectively, the Terrestrial Air Temperature and Precipitation: 1900–2017 Gridded Monthly Time Series, versions 5.01 (MATSUURA; WILLMOTT, 2009). The datasets have a worldwide monthly and yearly precipitation estimate at the $0.5° \times 0.5°$ level (0.5° corresponds to about 56 km). Estimates for each grid are based on an average of 20 nearby weather stations. First, using the municipality's centroid, the closest node in each square (Northeast, Northwest, Southwest, and Southeast) is identified. Then, the inverse square of the distance of the centroid from a node is used as a weight to calculate the average precipitation and temperature for the month. Finally, we construct yearly precipitation and temperature series for each municipality based on these weighted averages.

Table 2 – Summary statistics: Brazilian Semiarid Region, 2006-2017.

	Mean	SD	Min	Max	N
Credit (R$)	1,773,748	2,910,138	0	57,631,840	13,620
Credit Operations	282.85	277.92	0	3,124	13,620
Credit per capita (R$)	106.74	182.47	0	12,498.47	13,620
Credit Delinquency	203.89	295.38	0	4,243	13,620
GDP (R$ mil)	162,503.77	506,842.12	4,198.94	13,691,185.72	13,620
GDP per capita (R$ mil)	6,350.92	4,596.60	301.60	125,216.18	13,620
GDP Agricult. (R$ mil)	13,922.33	26,847.03	292.92	754,758.23	13,620
GDP Manuf. (R$ mil)	24,836.16	117,304.3	49.195	2,453,861	13,620
GDP Services. (R$ mil)	58,491.09	246,602.86	809.06	7,374,743.36	13,620
Per capita income (R$)	273.34	69.67	135.49	662.24	1,135
Gini index	0.52	0.05	0.36	0.79	1,135
Population	19,910.41	33,913.10	1,256	556,642	1,135
%Rural population	0.47	0.18	0.02	0.91	1,135
Years of schooling	9	0.77	6.34	10.97	1,135
%house with water	70.62	18.12	0.15	98.98	1,135
%houses with electricity	96.05	6.68	44.16	100	1,135
Illiteracy rate	29.98	6.33	9.59	47.38	1,135
Poverty rate	66.15	8.21	32.11	86.20	1,135
Firms	157.57	573	0	12,298	13,620
Jobs	1,816.07	6,146.43	0	124,594	13,620
Drough Shock	0.23	0.07	0.04	0.42	1,135
Precipitation	743.36	254.34	201.15	2,098.72	13,620
Temperature	25.17	1.79	19.49	31	13,620

Notes: This table shows summary statistics. The nominal variables are all deflated to Brazilian reais of 2010.

Table 2 presents the summary statistics of the main variables used in the thesis.

4 Drought Shock Measures

We measure the drought based on the ratio of average annual precipitation from 2012 to 2017 and the long-run average annual precipitation before the drought (1950-2011),

which is built from *the Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series*. The focus on rainfall is because this variable is crucially important for the water supply, and consequently for the configuration of a drought event. [7] Temperature is a control variable in the regression as discussed below.

There are two variables for the drought shock. The first is a continuous variable measuring the fluctuation of precipitation during drought. It is defined by the following equation:

$$\mathrm{DS_i} = 1 - \frac{\overline{R_i}^{12-17}}{\overline{R_i}^{H}}$$

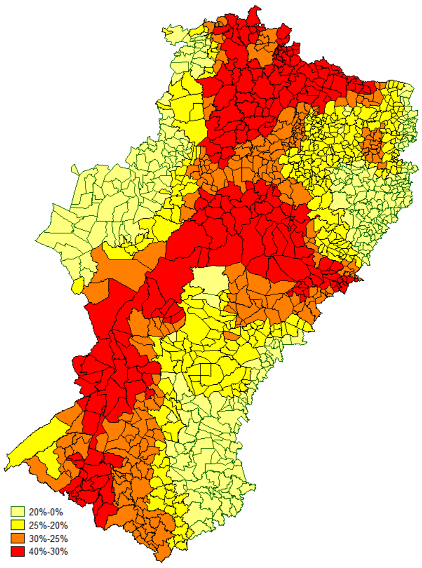
where $\overline{R_i}^{12}$ is average of rainfall intensity between 2012 and 2017 for municipality i, and $\overline{R_i}^{H}$ is historical average between 1950 and 2011 for municipality i. The $\mathrm{DS_i}$ is defined as one minus the fraction between the mean rainfall in the six years of drought and the historical average rainfall in municipality i. The variable range is between zero and one for the reason all localities had a decrease in average precipitation during the period. When the value tends to zero means that the municipalities did not have rainfall decrease concerning the historical average, but when the value tends to one means that the municipality was highly affected by the drought. A similar drought severity measure is presented in Dell (2012).

The spatial distribution of our drought shock measure (DS) is plotted in figure 2a. The inner municipalities show a greater decrease in rainfall than the municipalities on the border. Actually, we can be seen in figure 2c these localities also experienced low precipitations before the drought, but the relationship between localization and the drought is not certain. We just can conclude that the municipalities with lower rainfall are more likely to severe drought, but the time is determined for other factors.

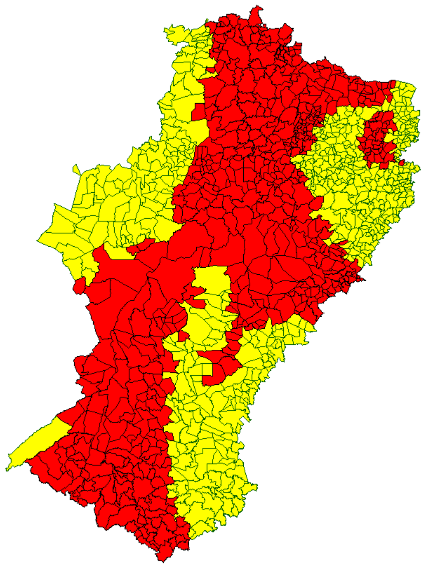
The second variable is a dummy designed to capture localities more exposure to the drought. We define an episode of drought shock in the following way: $D_i = 1$ if $\mathrm{DS_i} \in \mathrm{A} \cap \mathrm{B}$ where $\mathrm{A} = \{\mathrm{d_1, d_2, d_3, d_4, d_5, d_6, d_7, d_8, d_9, d_{10}}\}$, $\mathrm{B} = \{\mathrm{d_6, d_7, d_8, d_9, d_{10}}\}$ and $\mathrm{d_j}$ is decile $\{j\}$ of the distribution of $\mathrm{DS_i}$ values . In others words $\mathrm{D_i}$ =1 indicates that the municipality is among the 50% most affected by the drought. In Section 5.2.1, we discuss the reasons why we choose those specific deciles, in short, the comparison group is better based on observable characteristics. The spatial distribution of the dummy variable is plot in the figure 2b. As could be expected, inner localities are most affected, but there are municipality with dummy variable all over the semiarid territory.

[7] The water supply in a locality is determined by precipitation, surface water, and ground water, these two last are highly influenced by the first.

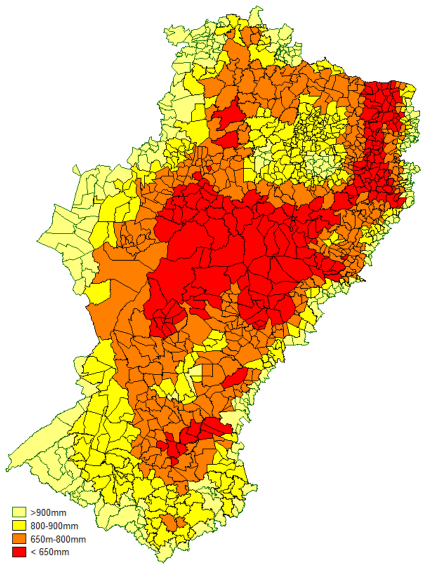
Figure 2 – Drought Exposure in Semiarid



(a) Continuos Variable



(b) Dummy Variable



(c) Historical Precipitation

Notes: These maps present a visualization of the exposure to the drought. The figure (a) plots 2012-2017 the percentage decrease of precipitation, following the scheme given in the legend. The figure (b) plots the dummy variable, where the red municipalities are the 50% most hit by the drought in semiarid and in yellow the least hit. The figure (c) show the the historical precipitation for each municipality.

5 Empirical Strategy

5 Research Design and Estimation

We aim to provide evidence on two questions: (1) How does extreme drought shock influence public credit allocation, credit delinquency rates, and local economic performance? (2) What is the effect of abundant public credit on the local economic performance during a drought shock?

5.1 Effect of drought shocks on local economic variables

In order to answer the first question, we explore the exogenous variation in weather. The literature has widely used this approach, especially using standard panel methods that aim to identify causal effects of weather variables in a range of outcomes (DELL; JONES; OLKEN, 2014). We use two sources of weather variation. First, we use an unanticipated shock determined by nature. Despite the recurrent low levels of rainfall in the semiarid region, the drought from 2012 to 2017 was unexpected due to its long duration - it was six years of rain far below the historical average. We also need the absence of severe drought in the municipality in the six years prior to 2012 to avoid any effect from previous events. On the other hand, there is also a variation in the *intensity* of the shock, which are the natural variations in rainfall in 1,135 municipalities during the period. Therefore, the main idea is to treat the drought first as a negative shock like a hurricane or flood, then as all municipalities were hit by drought, we explored drought exposure.

The main estimating equation takes the difference-in-difference specification:

$$\mathrm{Y}_{it} = \gamma_i + \lambda_t + \beta DS_i \times Post_t + \delta T_{it} + \tau_t^{'}\mathrm{X}_i + \epsilon_{it} \tag{1}$$

where Y_{it} is the outcome variable of municipality i and period t, γ_i and λ_t denotes municipal fixed effects and year fixed effects, DS_i is the continuous variable or dummy indicating drought shocks, T_{it} is the average of temperature of municipality i and period t , X_i is pre-treatment level of dependent variablel, geographical controls, and control variables (education, income and rural population), and ϵ_{it} standard errors. The dependent variables include BNB bank's loans, credit operations, delinquency rates, and measures of local economic performance such as municipal GDP, and employment. The time span goes from 2006 to 2017. The fixed effects γ_i for the municipalities absorb time-invariant characteristics, disentangling the shock from many possible sources of omitted variable bias. The time-fixed effects λ_t capture any common trends and thus help ensure that the effects are identified from idiosyncratic local shocks. The standard errors are clustered at the municipality level to account for serial correlation (BERTRAND; DUFLO; MULLAINATHAN, 2004)

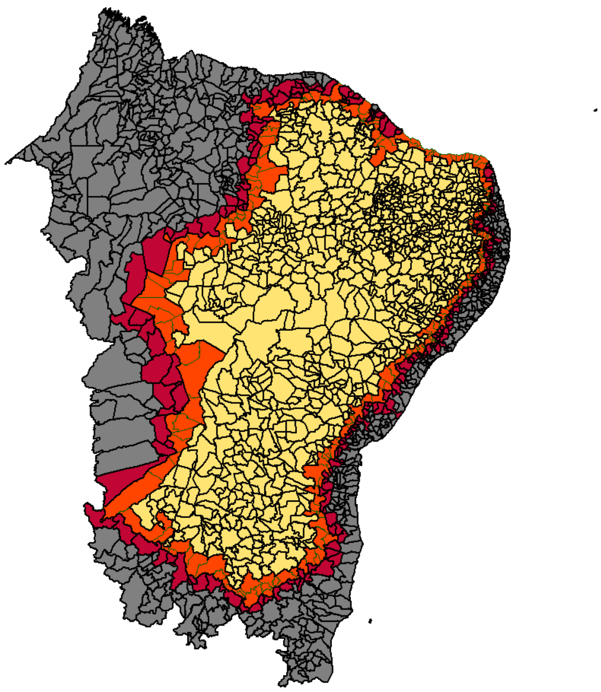
Our identification comes from the differential change in outcomes of municipalities with differing degrees of exposure to the drought. Given the time-varying controls, our identifying assumption is that municipalities are on similar trends regardless of the municipality was highly exposed to the drought or not. In other words, the identification assumption is that hardest-hit municipalities would have had a similar trend in the outcomes as those less-hit, in the absence of the drought.

5.2 Effect of an abundant public credit on local economic performance during a drought

To answer the second question, we explore a discontinuity in the public credit regime in which semiarid's municipalities operate under a more favorable credit supply. In short, borrowers in semiarid have a greater solvency bonus and a larger pool of credit because of the constitutional rule (see section 3.3). Municipalities did not influence the assignment of be located inside or outside the semiarid, thus could not determine their credit regime. The literature points out weather shocks are random draws that are transmitted in a given spatial area (DELL; JONES; OLKEN, 2014), so localities that have the proximity of each other tend to absorb the same weather shock. The identification strategy uses the fact that neighboring municipalities are exposed to common weather shocks, but at the same time they have similar geographical features, natural resources, and distance from the state capital. Thus, municipalities on the semiarid border had a similar drought shock, but they had different public credit supply. In the SUDENE area about 99% of municipalities had a negative deviation from the historical average in the period of analysis and all were hit by the drought shock - the difference is the drought intensity and the credit regime.

In the analysis, we select municipalities if they are at the border of the semiarid. There are 206 municipalities within and 224 out of semiarid delimitation. The municipalities inside are the treated group and the municipalities outside are the control group. The spatial distribution of municipalities on the semiarid border is plotted in figure 3.

Figure 3 – Municipalities on the semiarid border



Notes: The figure shows the location of municipalities on the semiarid border, the municipalities inside the semiarid border are orange (total of 206), and the municipalities outside are red (total of 224). The municipalities located in the semiarid but not in the frontier are in beige. Municipalities in beige and orange comprise the semiarid delimitation in 2011.

The main estimating equation is the following difference-in-differences specification:

$$Y_{it} = \gamma_i + \lambda_t + \beta SAR_i \times Post_t + \delta T_{it} + \tau_t^{'} X_i + \epsilon_{it} \tag{2}$$

where Y_{it} is the outcome variable of municipality i and period t, γ_i and λ_t denotes municipal fixed effects and year fixed effects, SAR_i is a dummy indicating that municipality is within semiarid, T_{it} is the average of temperature of municipality i and period t , X_i is pre-treatment level of dependent variablel, geographical controls, and control variables (education, income and rural population), and ϵ_{it} standard errors. The dependent variables include BNB bank's loans, credit operations, credit delinquency rates and measures of local economic performance as municipal GDP, and employment. The time span goes from 2006 to 2017. We add fixed effects γ_i to absorb time-invariant characteristics, and time-fixed effects λ_t to capture any common trends to all groups. The standard errors are clustered at the municipality level.

First, we test if border municipalities in semiarid received more loans from BNB bank - a positive result supports the assumption that semiarid have a more favorable credit supply during a drought. Second, we test if these municipalities have better economic performance during the drought shock. In other words, could the credit provided by the government bank assist these localities to support the drought shock? The analysis was split into two periods because the credit regime is changed with the solvency bonus differential was extinguished. The first period is from 2006 to 2013, and the second is from 2006 to 2017.

6 Assessing the Research Design

A concern about identification strategy is whether it is exogenous. In other words, for the first question, if a negative rainfall shock was independent of the specific characteristics of the municipalities. While for the second question, whether the delimitation of the semiarid was an exogenous criterion of municipality decision, that is, if the municipalities did not self-select before the drought.

The literature widely applies panel methods and explores weather variables' variation to estimate causal impacts on economic results (Chapter 3). These researchers argue that the use of climate realization over time in a given space unit is reliably identified because temperature, precipitation, and other climatic events vary plausibly and randomly over time (DELL; JONES; OLKEN, 2014). It is a fact that climatic characteristics can influence economic activities, especially in places highly dependent on agriculture, so we use panel data to control the fixed effects of time and location. In addition, to avoid concern about the endogeneity between climate and economic performance, the sample of municipalities is in a common climate area, the semiarid. Thus, we can assume without much concern that exposure to extreme weather events occurs regardless of the characteristics of the municipalities.

Bordering municipalities outside of semiarid delimitation are our control group in the analysis of the second question. Despite that, the average annual precipitation is the main criteria for inclusion, many localities are not included in the semiarid for small differences. Furthermore, the annual amounts of rainfall recorded in the municipalities until 1993 were used as a reference for the delimitation. However, climate change advancing also increased the intensity of drought in the last years, and the criteria for inclusion not

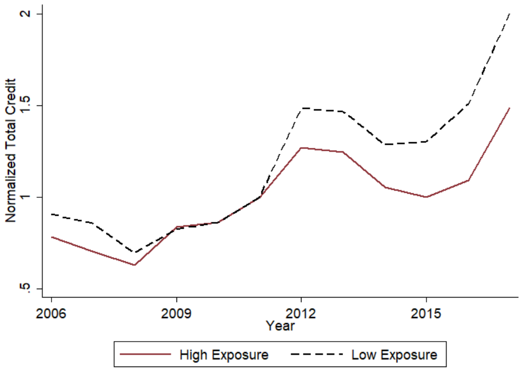
following the same pace. Seasonality is another big problem because in some regions rains with intensity just a few months of the year, and this criterion was not included. For example, an update delimitation in November 2017 included 73 new municipalities, but the previous update was in 2005.

In the following section, we present checks to assess if the treatment and control groups are comparable.

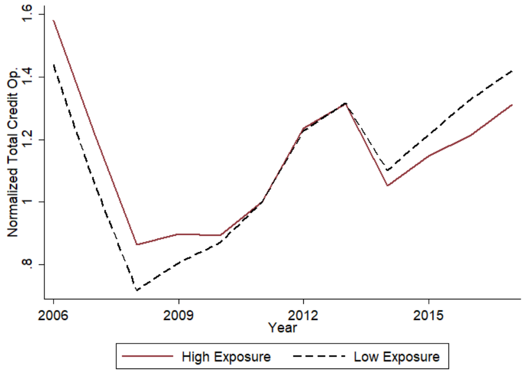
6.1 Control Group and Parallel Trends

The drought was not spread uniformly throughout the semiarid: some areas were more disproportionately affected than others. As shown in the figure 4, these areas correspondingly received less credit and experienced a relative decrease in gross locality product, but the number of formal jobs stayed stable. Also, we can observe that the dependent variables have the same trend in the period for both groups. For the second question, the figure 5 shows that the municipalities in semiarid receive a few more credit operations in the drought period, but for the other variables there is no variation between the groups.

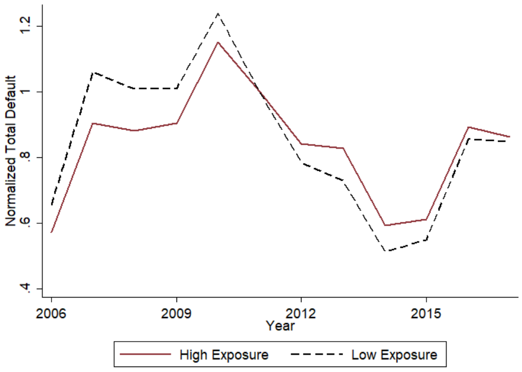
Figure 4 – Question 1: Normalized Dependent Variables in High vs. Low Exposure



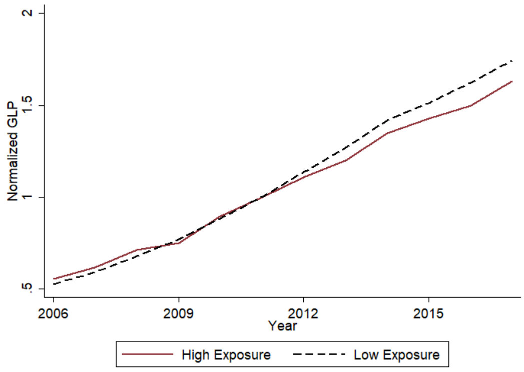
(a) Total Credit



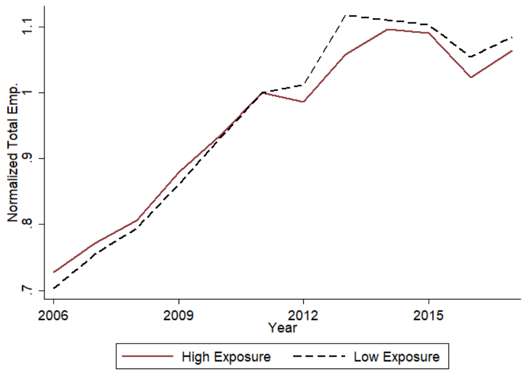
(b) Total Credit Operations



(c) Delinquency Rates



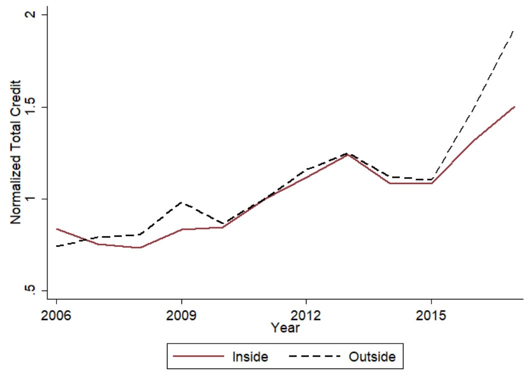
(d) Gross Domestic Product



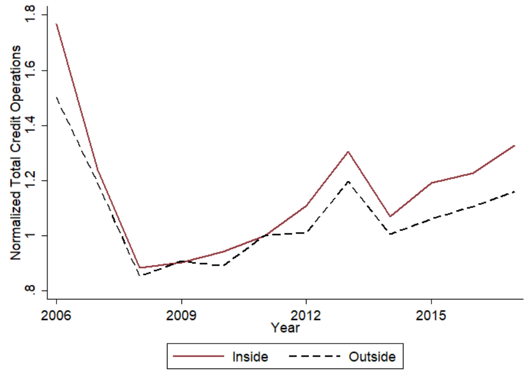
(e) Total Employment

Notes: This figure shows total real credit, credit operations, delinquency rates, municipal Gross Domestic Product, and employment, normalized to have value 1 in 2011, for municipalities with high versus low exposure to the drought. Localities are classified as having a high exposure if the municipality is in the group of 50% most hit. Yearly credit at the municipality level and GDP are deflated to Brazilian reais of 2010.

Figure 5 – Question 2: Normalized Dependent Variables in Inside vs. Outside

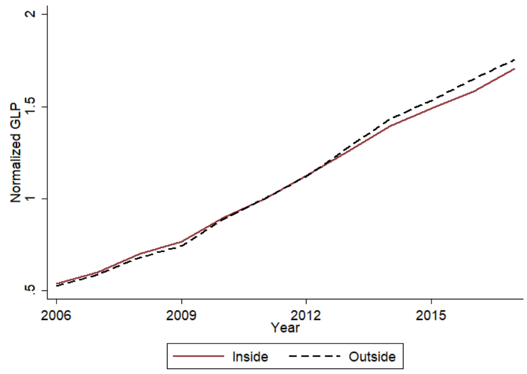


(a) Total Credit

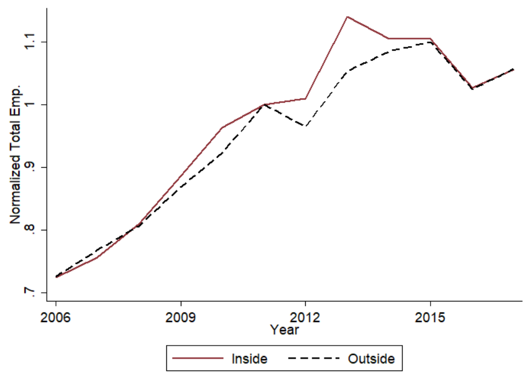


(b) Total Credit Operations

(c) Delinquency Rates



(d) Gross Domestic Product



(e) Total Employment

Notes: This figure shows total real credit, credit operations, delinquency rates, municipal Gross Domestic Product, and employment, normalized to have value 1 in 2011, for municipalities inside versus outside on the border of semiarid. Yearly credit at the municipality level and GDP are deflated to Brazilian reais of 2010.

As we use a difference-in-differences specification, our identifying assumption is that municipalities in semiarid would have had similar trends in outcomes in the absence of the drought shock, we will check formally for pre-trends in section 6.3. In order to verify whether treatment and control groups are balanced across pre-treatment observable

characteristics, we check for the overlap between these groups in the years before the drought. We test overlap for the dependent variables and other municipalities' features. Imbens e Wooldridge (2009) suggest a formally check for overlap using the standardized difference (STD), that for continuous variable it is given by:

$$\text{STD} = \frac{\mu_t - \mu_c}{\sqrt{\sigma_t^2 + \sigma_c^2}}$$

where μ_t and σ_t^2 are the mean and variance of treatement group, μ_c and σ_c^2 are the corresponding values for the municipalities for control group, STD below 0.25 evidence that the groups were balanced before the drought.

The table 3 shows the result of STD when the treatment group is the municipalities hardest hit by drought. As can be seen, municipalities less affected constitute a good control group based on observables. We also test what deciles produce the better comparison group based on observed variables. In the table, we show the results splitting the groups in 50%, 40%, 30%, and 20% most affected by the drought. Based on the STD results, the choice of the 50% most affected is superior to the others, because the STD is below 0.25 for all observable variables.

In order to assess the balanced in the groups related to question 2, the table 4 the table 4 reports the results and indicates the groups are balanced.

Table 3 – Question 1: Overlap between high exposure and low exposure groups

	(I) High Exposure 50% (n=567)	(II) Low Exposure 50% (n=568)	(III) High Exposure 40% (n=454)	(IV) Low Exposure 40% (n=681)	(V) High Exposure 30% (n=340)	(VI) Low Exposure 30% (n=795)	(VII) High Exposure 20% (n=227)	(VIII) Low Exposure 20% (n=908)
Credit Operations by BNB bank								
Avr	336.661	240.433	360.537	240.483	393.738	243.499	425.736	254.197
SD	356.672	230.807	377.280	231.460	383.103	250.205	391.450	267.418
Std Differences	.	0.227	.	0.271	.	0.328	.	0.362
Credit Oper by BNB bank per capita								
Avr	0.024	0.022	0.024	0.022	0.024	0.023	0.024	0.023
SD	0.024	0.020	0.024	0.020	0.026	0.020	0.024	0.022
Std Differences	.	0.065	.	0.059	.	0.056	.	0.042
Credit by BNB bank								
Avr	1193.014	748.673	1280.930	763.793	1427.286	775.356	1650.607	800.658
SD	1724.929	807.216	1855.484	837.624	2009.999	896.912	2269.544	947.500
Std Differences	.	0.233	.	0.254	.	0.296	.	0.346
Credit by BNB bank per capita								
Avr	73.862	65.420	73.553	67.027	73.322	68.061	77.558	67.657
SD	77.719	62.089	77.402	65.296	72.103	69.686	73.569	69.522
Std Differences	.	0.085	.	0.064	.	0.052	.	0.098
Years of schooling								
Avr	9.135	8.857	9.152	8.892	9.146	8.932	9.172	8.952
SD	0.764	0.754	0.765	0.759	0.746	0.774	0.741	0.773
Std Differences	.	0.259	.	0.241	.	0.198	.	0.205
Gini index								
Avr	0.520	0.515	0.520	0.515	0.520	0.516	0.523	0.516
SD	0.046	0.048	0.046	0.048	0.046	0.048	0.046	0.048
Std Differences	.	0.078	.	0.075	.	0.064	.	0.108
Poverty rate								
Avr	66.254	66.039	66.285	66.054	66.054	66.186	66.223	66.127
SD	8.275	8.166	8.104	8.297	8.158	8.248	8.818	8.065
Std Differences	.	0.018	.	0.020	.	-0.011	.	0.008
%house with water								
Avr	71.629	69.606	72.262	69.519	72.281	69.904	73.709	69.843
SD	17.679	18.524	17.290	18.596	17.363	18.408	15.850	18.580
Std Differences	.	0.079	.	0.108	.	0.094	.	0.158
%houses with electricity								
Avr	96.302	95.796	96.484	95.759	96.333	95.927	96.278	95.992
SD	5.663	7.570	4.928	7.628	5.074	7.269	4.598	7.115
Std Differences	.	0.054	.	0.080	.	0.046	.	0.034
%Rural population								
Avr	0.484	0.463	0.486	0.466	0.481	0.471	0.479	0.473
SD	0.178	0.187	0.175	0.188	0.170	0.188	0.180	0.184
Std Differences	.	0.082	.	0.081	.	0.038	.	0.024
Per capita income								
Avr	274.374	272.316	274.873	272.326	277.434	271.596	278.659	272.016
SD	69.678	69.767	67.130	71.392	68.614	70.128	75.372	68.187
Std Differences	.	0.021	.	0.026	.	0.060	.	0.065
Per capita GDP								
Avr	3401.534	2799.698	3563.409	2791.645	3787.899	2806.305	3978.783	2880.742
SD	4225.407	1054.209	4689.582	1024.415	5226.571	1303.152	5176.596	2243.011
Std Differences	.	0.138	.	0.161	.	0.182	.	0.195
Illiteracy rate								
Avr	28.916	31.039	28.742	30.803	28.150	30.760	27.839	30.513
SD	6.050	6.433	6.041	6.391	5.834	6.378	5.945	6.316
Std Differences	.	-0.240	.	-0.234	.	-0.302	.	-0.308
GDP Growth 2006-2011								
Avr	0.835	0.838	0.838	0.836	0.844	0.833	0.841	0.836
SD	0.285	0.365	0.301	0.344	0.309	0.335	0.318	0.330
Std Differences	.	-0.007	.	0.004	.	0.024	.	0.012
Growth Credit Operations 2006-2011								
Avr	1.421	0.752	1.697	0.678	2.068	0.665	0.686	1.186
SD	10.507	6.956	11.697	6.386	13.462	5.936	1.828	9.921
Std Differences	.	0.053	.	0.076	.	0.095	.	-0.050

Notes: We show four control group: (i) The most 50% municipalities affected by the drought (column I, the others 50%), (ii) The most 40% municipalities affected by the drought (column III, the others 60%), (iii) The most 30% municipalities affected by the drought (column V, the others 70%), and (iv) the most 20% municipalities affected by the drought (column VII, the others 80%). The control group in column II is our baseline control group. Columns in odd are the treatment groups and even are the control group.

Table 4 – Question 2: Overlap between inside and outside groups

	(I) Inside (n=206)	(II) Outside (n=224)
Credit Operations by BNB bank		
Avr	317.325	228.408
SD	377.008	258.135
Std Differences	.	0.195
Credit Oper by BNB bank per capita		
Avr	0.021	0.015
SD	0.021	0.020
Std Differences	.	0.204
Credit by BNB bank		
Avr	1164.961	1138.727
SD	2010.084	2492.384
Std Differences	.	0.008
Credit by BNB bank per capita		
Avr	66.901	58.650
SD	67.352	111.191
Std Differences	.	0.063
Years of schooling		
Avr	8.910	8.879
SD	0.755	0.803
Std Differences	.	0.029
Gini index		
Avr	0.519	0.531
SD	0.046	0.052
Std Differences	.	-0.177
Poverty rate		
Avr	66.284	66.276
SD	8.281	12.399
Std Differences	.	0.001
%house with water		
Avr	76.393	82.530
SD	13.257	11.271
Std Differences	.	-0.353
%houses with electricity		
Avr	95.984	95.526
SD	6.244	6.287
Std Differences	.	0.052
%Rural population		
Avr	0.458	0.402
SD	0.190	0.206
Std Differences	.	0.200
Per capita income		
Avr	277.491	293.144
SD	71.013	118.740
Std Differences	.	-0.113
Per capita GDP		
Avr	3860.410	4510.437
SD	5514.312	6329.905
Std Differences	.	-0.077
Illiteracy rate		
Avr	30.161	26.802
SD	6.437	8.283
Std Differences	.	0.320
GDP Growth 2006-2011		
Avr	0.826	0.924
SD	0.294	1.101
Std Differences	.	-0.086
Growth Credit Operations 2006-2011		
Avr	0.771	2.277
SD	3.747	17.296
Std Differences	.	-0.085

Notes: Columns I is the treatment group, i.e, the 204 municipalities inside the border of semiarid, and in column II the control group, which are 224 municipalities outside the border of semiarid.

6 Results

7 Effect of drought shocks on local economic variables

7.1 Effects on Credit and Delinquency Rates

First, we look for empirical evidence of the effect of drought shock on the public credit and delinquency for municipalities in semiarid Brazil. As discussed in Section 3.3 the BNB bank is the most important public bank for the region, thus the variables are referring to this bank. Our dependent variables are the municipal total credit, credit operations, delinquency rates of credit operations, and total sectoral credit. The results of the estimation of equation 1 are reported in table 5 with each dependent variable in a different column.

Estimates imply that droughts shocks significantly affect the credit variables. Coefficients are negative and statistically significant. Moreover, they show that for the most affected municipalities the total credit and credit operation decreased respectively by 11% and 17% during the years of severe water scarcity. The estimates of continuous measure also show that a fall of 10% in rainfall about the historical average decreases the total credit and credit operation respectively by 10% and 13%.

When we disaggregate loans by sector, we find significant and negative impact only on the livestock sector - this result is consistent with the high presence of livestock producers in the semiarid (Section 3.1). However, a concern is that the results for the agriculture sector are not significant, even the sector has also been important for the region. Furthermore, as pointed for the literature (Chapter 2) the agriculture is highly impacted by the variation in rainfall. Possibly, the agriculture sector in the semiarid has others cope mechanisms to drought, as crop insurance or a more adaptative response to extreme droughts, like a change in crop mix. More investigation for these facts is important for more formal conclusions.

The result for the service is also intriguing because the sector has a positive and significant impact. There are two possible assumptions for this fact: first, as BNB has an important credit portfolio allocated for microentrepreneurs, possibly some producers may have shifted the economic activity from livestock to services as coping strategies to the drought. On the other hand, the BNB bank may have shifted the credit from the livestock sector for services for considering the sector less risky. The first movement on credit allocation is a demand-side, and the second is the result of the supply-side.

The result on manufacturing was also surprising, the drought shock increases the credit flow for the sector, although it is significant only for dummy variable. The result possibly was driven by the supply-side, the producers on manufacturing are more inserted on the formal market, and possibly have more assets than the livestock producers, as a result of the drought shock the loan for the manufacturing sector may be perceived as less risky and the credit may have shifted for the sector.

A relevant concern about the fall in total credit as drought effect is whether the result is led by the BNB bank's behavior, i.e, an increase in the delinquency arise from the decreased rainfall may result in riskier loans. The estimates on total default of credit

operations reported in column (3) show positive and significant effects for both drought shock variables. Thus, the decrease in credit may not only be driven by the fall of economic activity (the demand side) but also by the BNB (supply side) - this aspect is particularly relevant because the credit supply may have an important role to cope of the negative shock, especially in low-income areas that often exhibit constraints credit. For this reason, we investigate in the following section the effect of abundant public credit on the local economic performance during a drought shock.

Table 5 – BNB Results

	All Sectors			Results by Sector			
	Credit	Credit Operations	Credit Delinquen-cies	Agriculture	Livestock	Manufact.	Services
Drought Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Continuous	-1.0059***	-1.3140***	1.3934***	-0.0479	-1.6926***	1.7609	1.9257*
	(0.3283)	(0.2905)	(0.2135)	(1.1057)	(0.4496)	(1.1128)	(1.1602)
Dummy	-0.1189***	-0.1739***	0.1668***	0.1373	-0.1487**	0.3153**	0.4182***
	(0.0443)	(0.0376)	(0.0302)	(0.1557)	(0.0593)	(0.1561)	(0.1510)
Observations	13,620	13,620	13,620	13,620	13,620	13,620	13,620
Number of municipalities	1,135	1,135	1,135	1,135	1,135	1,135	1,135
Geographical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the estimation of Equation 1. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the natural logarithm of total credit, credit operation, delinquency rates of credit operations, and sectoral credit in each municipality. The independent variables are a continuous variable that measures the fluctuation of precipitation during drought, and the dummy variable indicates that municipalities are among the 50% most affected by drought. All regressions include fixed effects of municipality and year. The controls are as follows: geographic controls (latitude and longitude), initial conditions, education, income, rural population, and average annual temperature.

7.2 Effects on Gross Domestic Product

We now investigate if the decrease in rainfall is associated with an impact on the GDP. Estimates of equation 1 are in table 6. The sectoral local GDP in Brazil is disaggregated into local manufacturing, services, and agricultural GDPs. However, we are not able to disaggregate into farming GDP and livestock GDP, then we presented the combined result of local agriculture GDP.

The results for all sectors are negative and statistically significant for both total GDP and per capita GDP. The results show that for the most affected municipalities the total GDP and per capita GDP decreased by 1% during the years of severe water scarcity. The estimates of continuous variables also show that a fall of 10% in rainfall about the historical average decreases the total GDP and per capita GDP by 1%.

When we disaggregate GDP, we find a significant impact only for continuous variable on the Manufacturing sector at a 10% significance level. This result may be driven by firms in the food sector, where the yield is highly dependent on water supply (BLACKHURST; HENDRICKSON; VIDAL, 2010). The impact only for this sector and not for the agriculture sector may indicate presumably that the agriculture sector has a coping strategy to the drought while the manufacturing sector was highly affected even receiving more credit. It is also important to highlight that the manufacturing in semiarid is a small sector, then the marginal variations may show significant results.

Possibly, the result significative for all sectors is because the minimum detectable

effect on GDP is only verified jointly.

Table 6 – GDP Results

	All Sectors		Results by Sector		
	Total GDP	GDP per capita	Agriculture	Manufact.	Services
Drought Variables	(1)	(2)	(3)	(4)	(5)
Continuous	-0.1785**	-0.1226*	-0.2101	-0.3781*	0.0436
	(0.0693)	(0.0627)	(0.1706)	(0.2035)	(0.0691)
Dummy	-0.0160*	-0.0179**	-0.0008	-0.0398	0.0094
	(0.0093)	(0.0086)	(0.0211)	(0.0289)	(0.0107)
Observations	13,620	13,620	13,620	13,620	13,620
Number of municipalities	1,135	1,135	1,135	1,135	1,135
Geographical Controls	Yes	Yes	Yes	Yes	Yes
Initial Conditions	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the estimation of Equation 1. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the natural logarithm of GDP, GDP per capita, and sectoral GDP in each municipality. The independent variables are a continuous variable that measures the fluctuation of precipitation during drought, and the dummy variable indicates that municipalities are among the 50% most affected by drought. All regressions include fixed effects of municipality and year. The controls are as follows: geographic controls (latitude and longitude), initial conditions, education, income, rural population, and average annual temperature.

7.3 Effects on Formal Sector

Now, we look for empirical evidence of the effect of drought shock on other indicative of local economic performance. We investigate the level of jobs in the formal sector for all sectors and by agriculture, manufacturing, services, trade, and public administration, here we are not also able to disaggregate into farming and livestock. Even though the informal sector is important for the regions there are no data for this investigation.

The table 7 report the results of estimation of equation 1. The coefficient for all sectors is not statistically significant. When investigating the disaggregated data the result is significant for both variables just on the manufacturing sector, the result is positive and may have been driven by the increase of credit, but as aforementioned, small changes in the sector result in meaningful effects. Inclusive for the most important sector of the region, agriculture, the result is not significant and shows that possibly the formal sector has coping strategies to the drought shocks.

Table 7 – Formal Sector Results

	All Sectors	Results by Sector				
Drought Variables	Jobs (1)	Agriculture (2)	Manufacturing (3)	Services (4)	Trade (5)	Public Adm (6)
Continuous	0.1214	-0.1401	1.3291***	0.3612	0.2301	-0.3363
	(0.1204)	(0.3059)	(0.3520)	(0.2407)	(0.1427)	(0.3099)
Dummy	0.0085	-0.0049	0.1731***	0.0267	0.0551**	-0.0397
	(0.0156)	(0.0384)	(0.0507)	(0.0331)	(0.0215)	(0.0400)
Observations	13,620	13,620	13,620	13,620	13,620	13,620
Number of municipalities	1,135	1,135	1,135	1,135	1,135	1,135
Geographical Controls	Yes	Yes	Yes	Yes	Yes	Yes
Initial Conditions	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the estimation of Equation 1. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the natural logarithm of total Jobs, Agriculture, Manufacturing, Services, Trade, and Public Administration in each municipality. The independent variables are a continuous variable that measures the fluctuation of precipitation during drought, and the dummy variable indicates that municipalities are among the 50% most affected by drought. All regressions include fixed effects of municipality and year. The controls are as follows: geographic controls (latitude and longitude), initial conditions, education, income, rural population, and average annual temperature.

8 Effect of abundant public credit on the local economic performance during a drought shock

In this section, we investigate question 2. The analysis is split into two different periods, because of the change in credit regime in 2013. In panel A the period is from 2006 to 2017 while in panel B is from 2006 to 2013.

8.1 Effects on Credit and Delinquency Rates

First, to provide empirical evidence that producers in the semiarid have abundant public credit during the drought, we estimative the equation 2 for total credit, credit operation, total default of credit operations, and total sectoral credit. The table 8 showed the results. For panel A the results are statistically significant only for Livestock, the producers inside semiarid have about 16% more credit than the outside. For panel B, the results are statistically significant both for total credit, credit operation, and livestock, the magnitude of coefficients are respectively by 16%, 17%, and 18%. The result corroborating the assumption that semiarid have more a more favorable credit supply.

8.2 Effects on Gross Domestic Product

Now, we evaluate if being inside of a region with abundant public credit has an impact on the local GDP during a drought shock. Our dependent variable is total GDP, GDP per capita, and sectoral GDP. The result is reported in tables 9. For panels A and B, the results are only statistically significant for total GDP and per capita GDP, but the impact is negative, which means that despite that municipalities receive more credit, they did not have a better performance during the drought. In the semiarid, municipalities

Table 8 – BNB Results

	All Sectorss			Results by Sector			
	Credit	Credit Operations	Credit Delinquencies	Agriculture	Livestock	Manufact.	Services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
Semiarid	0.0573	0.1036	0.0275	-0.0551	0.1641*	-0.1081	-0.1799
	(0.0644)	(0.0654)	(0.0542)	(0.2292)	(0.0959)	(0.2724)	(0.2719)
Observations	5,160	5,160	5,160	5,160	5,160	5,160	5,160
Panel B							
Semiarid	0.1572**	0.1685***	0.0044	0.2062	0.1801*	-0.0520	-0.1430
	(0.0625)	(0.0601)	(0.0545)	(0.2796)	(0.0939)	(0.3223)	(0.3633)
Observations	3,440	3,440	3,440	3,440	3,440	3,440	3,440
Number of municipalities	430	430	430	430	430	430	430
Geographical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the estimation of Equation 2. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. In Panel A the regressions are for 12 years (from 2006 to 2017). In Panel B the regressions are for 8 years (from 2006 to 2013). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the natural logarithm of total credit, credit operation, total delinquency rates of credit operations, and total sectoral credit in each municipality. The independent variable is a dummy variable that indicates that municipalities are inside of semiarid. All regressions include fixed effects of municipality and year. The controls are as follows: geographic controls (latitude and longitude), initial conditions, education, income, rural population, and average annual temperature.

have a decrease of total GDP by 3%-6%, and for GDP per capita by 5%-7% during the drought. The future investigation may provide empirical evidence for this, for example, the BNB did not choose the borrowers with more credit constraints as a result of the drought, maybe the public credit did not use for assisting the most vulnerable people as informal or family farming, these questions are important in the context of climate change and development.

8.3 Effects on Formal Sector

Now, we investigate other variables to local economies' performance: the level of jobs in the formal sector, first for all sectors, and second by sectors. The results are reported in table 10. The estimations are not statistically significant for all dependent variables. The result is expected because the drought shock has not affected on formal sector, then the abundant public credit is not crucial for the sector.

Table 9 – GDP Results

	All Sectorss		Results by Sector		
	Total GDP	GDP per capita	Agriculture	Manufact.	Services
	(1)	(2)	(3)	(4)	(5)
Panel A					
Semiarid	-0.0346*	-0.0547***	0.0031	-0.0249	-0.0218
	(0.0198)	(0.0200)	(0.0357)	(0.0459)	(0.0194)
Observations	5,160	5,160	5,160	5,160	5,160
Panel B					
Semiarid	-0.0621**	-0.0730**	0.0132	-0.0554	-0.0313**
	(0.0288)	(0.0362)	(0.0409)	(0.0366)	(0.0136)
Observations	3,440	3,440	3,440	3,440	3,440
Number of municipalities	430	430	430	430	430
Geographical Controls	Yes	Yes	Yes	Yes	Yes
Initial Conditions	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the estimation of Equation 2. Robust standard errors (in parentheses) are clustered at the municipal level. In Panel A the regressions are for 12 years (from 2006 to 2017). In Panel B the regressions are for 8 years (from 2006 to 2013). Significance *** p < 0.01, ** p < 0.05, * p < 0.1. The dependent variables are the natural logarithm of GDP, GDP per capita, and sectoral GDP in each municipality. The independent variable is a dummy variable that indicates that municipalities are inside of semiarid. All regressions include fixed effects of municipality and year. The controls are as follows: geographic controls (latitude and longitude), initial conditions, education, income, rural population, and average annual temperature.

Table 10 – Formal Sector Results

	All Sectors	Results by Sector				
	Jobs	Agriculture	Manufacturing	Services	Trade	Public Adm
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Semiarid	-0.0187	-0.0041	-0.0258	-0.0476	-0.0062	-0.0864
	(0.0259)	(0.0603)	(0.0932)	(0.0479)	(0.0304)	(0.0744)
Observations	5,160	5,160	5,160	5,160	5,160	5,160
Panel B						
Semiarid	-0.0176	-0.0582	-0.0785	-0.0479	0.0202	-0.1247
	(0.0273)	(0.0632)	(0.0982)	(0.0444)	(0.0293)	(0.1376)
Observations	3,440	3,440	3,440	3,440	3,440	3,440
Number of municipalities	430	430	430	430	430	430
Geographical Controls	Yes	Yes	Yes	Yes	Yes	Yes
Initial Conditions	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the estimation of Equation 2. Robust standard errors (in parentheses) are clustered at the municipal level. In Panel A the regressions are for 12 years (from 2006 to 2017). In Panel B the regressions are for 8 years (from 2006 to 2013). Significance *** p < 0.01, ** p < 0.05, * p < 0.1. The dependent variables are the natural logarithm of total Jobs, Agriculture Jobs, Manufacturing Jobs, Services Jobs, Trade Jobs, and Public Administration Jobs in each municipality. The independent variable is a dummy variable that indicates that municipalities are inside of semiarid. All regressions include fixed effects of municipality and year. The controls are as follows: geographic controls (latitude and longitude), initial conditions, education, income, rural population, and average annual temperature.

9 Dynamic Difference-in-Differences Analysis

For performing a formal check, we investigate from the dynamic difference-indifferences whether there are pre-trends in the dependent variables. Furthermore, the analysis could provide more understanding of the drought effect over time. The main estimation equation is:

$$\mathrm{Y}_{it} = \alpha + \gamma_i + \lambda_t + \sum_{k<0} \beta_k \mathrm{D}'_{it} + \sum_{k>0} \beta_k \mathrm{D}'_{it} + \epsilon_{it} \tag{3}$$

$$\mathrm{D}'_{it} = 1[t - 2011 = k]$$

For question 1 the sample consists of the semiarid's municipalities and the treatment group is the municipalities with high exposure to drought - 50% of the most affected municipalities. We can see in figure 6 and table 11 the results for the variables total credit, delinquency rates, GDP and jobs. Note that, the figure 6 presents pre-trends in some years, but it is important to remember that the semiarid is a region susceptible to recurrent drought (LIMA; MAGALHÃES, 2018), often with a duration of one or two years and not a severe drought of six years as our analysis' period, however, these previous droughts may influence the variables' outcomes, the effect of droughts may overlap during the years and be captured for our estimates.

Estimates for credit pointed to a drop in this variable after the drought and the effect increased over time. The results of the previous years are not significant except the year 2006. Many events happened in those previous years, such as changes in the delimitation of SUDENE, so our result might not be so clear.

Table A.1 in Appendix A show the results for different specifications - the inclusion of pre-treatment level of dependent variable, geographical controls, and control variables. The results are not different from the main specification. We also show in table A.2 the results by sectors, we can conclude that the livestock drove the results.

For the delinquency rates, we can see that there is a growing trend that could be interpreted as a failure of the well-known "parallel trends" assumption, so the results of differences-in-differences could be viewed with caveats. The results in table A.3 show that there are no significant changes for different specifications.

Estimates for the GDP showed a decrease in these variables after the drought, but the coefficients for 2014 and 2017 are not significant. The coefficients of previous years are not also statistically different from zero for most years, but for 2008 and 2009 presented, respectively, a significant increase and decrease. The results in table A.4 for different specifications show that there are no significant changes. The results by sector in table A.5 show that the negative impact after the drought is not driven by the agriculture sector but by the other sectors.

Effects on employment are not statistically different from zero. The results in table A.6 and A.7 presented that there are no significant changes for different specifications or sectors.

For question 2 the sample consists of the municipalities at the border of the semiarid and the treatment group is the municipalities inside the semiarid. We can observe in figure 7 and table 12 that most coefficients are not statistically different of zero, just for the variable total credit and delinquency rates.

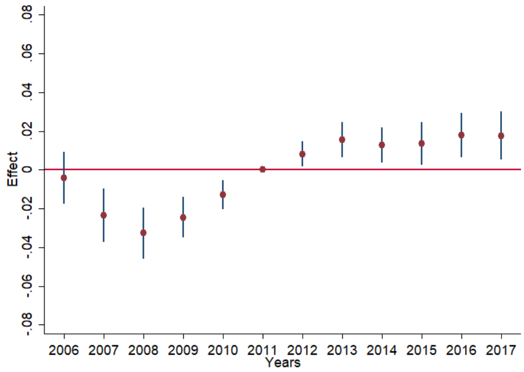
Estimates for credit point to an increase in this variable after the drought only for 2012 and 2013, before the change in credit regime, then evidence that producers in the semiarid have abundant public credit during the drought only these two years. The results of the previous years are not significant except the year 2006 with positive effect. The results in table B.1 (Appendix B) for different specifications show that there are no significant changes. The results by sector in table B.2 presented that the positive impact after the drought was driven by the livestock and services.

For the delinquency rates, the results are significant only for 2014 and 2015, these results may be a consequence of the Brazilian economic crisis of 2014-2017 or the change in the 2013 credit regime. For this reason, these results should be seen with caveats. The results in table B.3 for different specifications show that there are no significant changes.

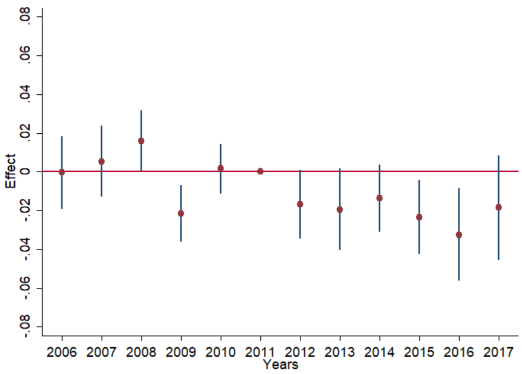
Effects on GDP and employment are not statistically different from zero. The results in tables B.4, B.5, B.6, and B.7 show that there are no significant changes for different specifications or sectors.

Figure 6 – Question 1: Dynamic Difference-in-Differences Analysis

(a) Total Credit



(b) Delinquency Rates



(c) Gross Domestic Product

(d) Total Employment

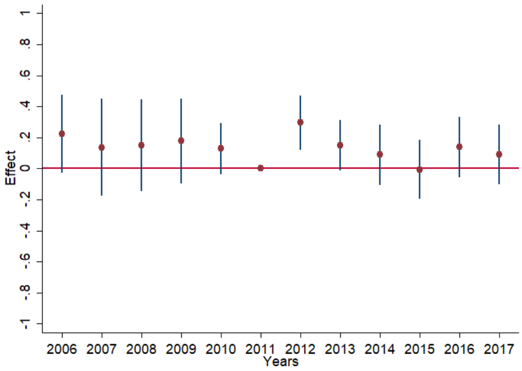
Notes: This figure presents the results of the estimation of equation 3 for the main dependent variables. The sample are the 1,135 municipalities in Brazilian Semiarid region.

Table 11 – Question 1: Dynamic Difference-in-Differences Analysis

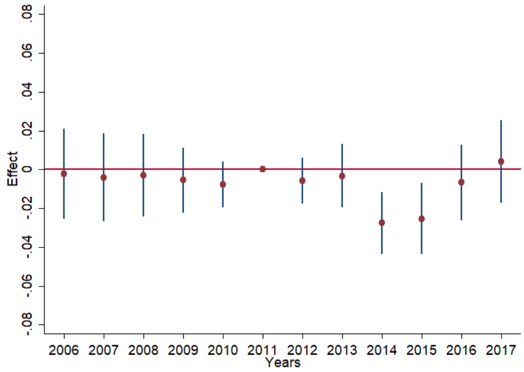
	(1) Credit	(2) Delinquency	(3) GDP	(4) Jobs
High Exposure x (Year= 2006)	-0.1666**	-0.0041	-0.0004	-0.0268
	(0.0693)	(0.0068)	(0.0096)	(0.0264)
High Exposure x (Year= 2007)	-0.1254	-0.0233***	0.0055	-0.0144
	(0.0793)	(0.0070)	(0.0094)	(0.0252)
High Exposure x (Year= 2008)	0.0827	-0.0327***	0.0160**	-0.0204
	(0.1014)	(0.0067)	(0.0080)	(0.0267)
High Exposure x (Year= 2009)	0.0373	-0.0245***	-0.0215***	0.0351
	(0.0793)	(0.0054)	(0.0074)	(0.0230)
High Exposure x (Year= 2010)	0.0148	-0.0128***	0.0017	0.0280
	(0.0437)	(0.0037)	(0.0065)	(0.0261)
High Exposure x (Year= 2012)	-0.1179**	0.0083**	-0.0169*	-0.0143
	(0.0463)	(0.0033)	(0.0090)	(0.0200)
High Exposure x (Year= 2013)	-0.1499***	0.0155***	-0.0194*	-0.0211
	(0.0500)	(0.0046)	(0.0108)	(0.0261)
High Exposure x (Year= 2014)	-0.2434***	0.0130***	-0.0135	0.0049
	(0.0488)	(0.0046)	(0.0088)	(0.0253)
High Exposure x (Year= 2015)	-0.2668***	0.0135**	-0.0233**	-0.0074
	(0.0530)	(0.0056)	(0.0097)	(0.0214)
High Exposure x (Year= 2016)	-0.2729***	0.0178***	-0.0324***	0.0158
	(0.0532)	(0.0059)	(0.0121)	(0.0267)
High Exposure x (Year= 2017)	-0.3123***	0.0177***	-0.0185	-0.0093
	(0.0535)	(0.0064)	(0.0138)	(0.0241)
Observations	13,620	13,620	13,620	13,620
Number of municipalities	1,135	1,135	1,135	1,135
Geographical Controls	No	No	No	No
Initial Conditions	No	No	No	No
Temperature	No	No	No	No
Control Variables	No	No	No	No
Municipality & Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the natural logarithm of total credit, delinquency rates, GDP, and the total formal jobs in each municipality. All regressions include municipality and year fixed effects. The sample is the 1,135 municipalities in Brazilian Semiarid region.

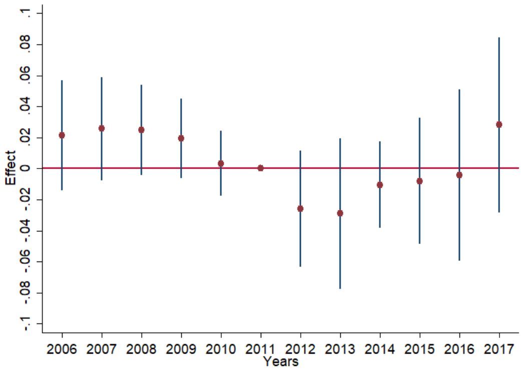
Figure 7 – Question 2: Dynamic Difference-in-Differences Analysis



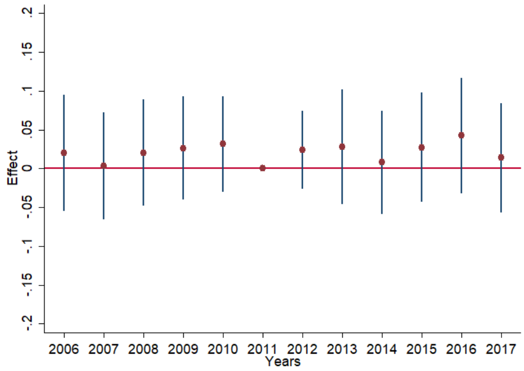
(a) Total Credit



(b) Delinquency Rates



(c) Gross Domestic Product



(d) Total Employment

Notes: This figure presents the results of the estimation of equation 3 for the main dependent variables. The sample are the 430 municipalities at the border of the semiarid.

Table 12 – Question 2: Dynamic Difference-in-Differences Analysis

	(1) Credit	(2) Delinquency	(3) GDP	(4) Jobs
Inside x (Year= 2006)	0.2258*	-0.0022	0.0215	0.0204
	(0.1279)	(0.0118)	(0.0180)	(0.0380)
Inside x (Year= 2007)	0.1371	-0.0040	0.0257	0.0036
	(0.1589)	(0.0115)	(0.0168)	(0.0352)
Inside x (Year= 2008)	0.1494	-0.0029	0.0248*	0.0204
	(0.1500)	(0.0108)	(0.0147)	(0.0347)
Inside x (Year= 2009)	0.1785	-0.0055	0.0194	0.0262
	(0.1394)	(0.0085)	(0.0130)	(0.0338)
Inside x (Year= 2010)	0.1285	-0.0077	0.0034	0.0316
	(0.0839)	(0.0061)	(0.0106)	(0.0314)
Inside x (Year= 2012)	0.2963***	-0.0059	-0.0260	0.0246
	(0.0885)	(0.0060)	(0.0191)	(0.0256)
Inside x (Year= 2013)	0.1499*	-0.0032	-0.0290	0.0282
	(0.0831)	(0.0083)	(0.0247)	(0.0377)
Inside x (Year= 2014)	0.0897	-0.0275***	-0.0104	0.0081
	(0.0986)	(0.0081)	(0.0141)	(0.0339)
Inside x (Year= 2015)	-0.0062	-0.0253***	-0.0080	0.0274
	(0.0966)	(0.0094)	(0.0207)	(0.0360)
Inside x (Year= 2016)	0.1394	-0.0067	-0.0043	0.0426
	(0.0993)	(0.0100)	(0.0280)	(0.0379)
Inside x (Year= 2017)	0.0911	0.0042	0.0283	0.0139
	(0.0976)	(0.0108)	(0.0287)	(0.0359)
Observations	5,160	5,160	5,160	5,160
Number of municipalities	430	430	430	430
Geographical Controls	No	No	No	No
Initial Conditions	No	No	No	No
Temperature	No	No	No	No
Control Variables	No	No	No	No
Municipality & Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the natural logarithm of total credit, delinquency rates, GDP, and the total formal jobs in each municipality. All regressions include municipality and year fixed effects. The sample is the 430 municipalities at the border of the semiarid.

7 Conclusion

The two questions presented in this thesis have investigated the possible impacts of drought shocks on local economic performances and the relations with credit provided by the state-owned bank. The aim was also to understand the mechanisms behind these relationships, to contribute to building better policies to mitigate the negative impacts of extreme weather events.

The first question contributes to evaluate the effect of rainfall shocks on credit, delinquency rates, and measures of local economic performance in municipalities of the Brazilian Semiarid region. We show that negative rainfall shocks are significantly associated with lower loans derived from BNB, especially for those engaged with livestock activities. This is expected given that a considerable fraction of the population in this region depends on farming and livestock for a living. On the other hand, the drought shock is also associated with an increase in delinquency rates - thus, the decrease in credit may be a BNB's behavior that considering the loans riskier for the localities most affected by the drought. This result has important implications for development issues, mostly in the context of climate change, because credit may be a coping strategy to weather shocks. We also find that drought shocks are associated with a decrease in municipal GDP, by contrast, no effects on the formal sector were reported. This evidence implies that the negative result in GDP may be driven by the informal sector but further analysis in the future is necessary for a formal conclusion.

The second question examined an important economic development issue: May abundant public credit assist localities during the drought shocks? We provide evidence for the mechanisms through which the localities are exposed to different credit regimes but at the same time are hit by the same weather shock. The results show that municipalities with abundant credit did not have better economic performance. This effect combined with the concerns about the BNB'S behavior arises important questions about the allocation of public credit during the drought. Potentially, the public credit was not driven for assisting the most vulnerable people during the drought as informal workers or to family farming.

These effects have important implications for public policy since that the main source of resource for the credit provided by BNB bank was the FNE - the main Regional Policy in Brazil. Once that the credit may be a coping strategy for these shocks, the expected was the municipalities more hit received credit and that the abundant credit would provide greater performances during the drought, but that didn't happen. The results raise questions about the actuation of the public policy in the context of extreme weather events because demonstrate, first that the BNB has a behavior similar to the private banks, and, second the resources cannot provide support for the municipalities. Concerns about the way the public credit is allocated are relevant, but in the context of more frequent extreme weather events, public policy that incentive people to stay in climate-vulnerable areas may not be always the best adaptation policy.

These two questions try to uncover important topics related to weather shocks. The results of this study provide local effects of the impacts of rainfall scarcity in the context of a developing country. However, there are still countless open questions to be investigated for more formal conclusions.

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APPENDIX A: Question 1: Dynamic Difference-in-Differences Analysis

Table A.1 – Question 1: Effects on Credit

	(1) Credit	(2) Credit	(3) Credit	(4) Credit	(5) Credit
High Exposure x (Year= 2006)	-0.1666**	-0.1630**	-0.1960**	-0.1965**	-0.1893**
	(0.0693)	(0.0722)	(0.0770)	(0.0770)	(0.0776)
High Exposure x (Year= 2007)	-0.1254	-0.0721	-0.1058	-0.1061	-0.1179
	(0.0793)	(0.0839)	(0.0845)	(0.0844)	(0.0860)
High Exposure x (Year= 2008)	0.0827	0.1528	0.1276	0.1276	0.1323
	(0.1014)	(0.1111)	(0.1124)	(0.1124)	(0.1178)
High Exposure x (Year= 2009)	0.0373	0.0342	0.0159	0.0161	0.0010
	(0.0793)	(0.0843)	(0.0862)	(0.0861)	(0.0848)
High Exposure x (Year= 2010)	0.0148	0.0075	-0.0048	-0.0040	-0.0034
	(0.0437)	(0.0455)	(0.0457)	(0.0460)	(0.0469)
High Exposure x (Year= 2012)	-0.1179**	-0.1335***	-0.1286***	-0.1274***	-0.1145**
	(0.0463)	(0.0456)	(0.0455)	(0.0457)	(0.0456)
High Exposure x (Year= 2013)	-0.1499***	-0.1489***	-0.1316***	-0.1301***	-0.1228**
	(0.0500)	(0.0491)	(0.0481)	(0.0485)	(0.0487)
High Exposure x (Year= 2014)	-0.2434***	-0.2488***	-0.2278***	-0.2266***	-0.2233***
	(0.0488)	(0.0491)	(0.0495)	(0.0498)	(0.0506)
High Exposure x (Year= 2015)	-0.2668***	-0.2663***	-0.2368***	-0.2343***	-0.2171***
	(0.0530)	(0.0514)	(0.0506)	(0.0518)	(0.0534)
High Exposure x (Year= 2016)	-0.2729***	-0.2740***	-0.2382***	-0.2363***	-0.2270***
	(0.0532)	(0.0522)	(0.0511)	(0.0517)	(0.0519)
High Exposure x (Year= 2017)	-0.3123***	-0.3122***	-0.2849***	-0.2833***	-0.2709***
	(0.0535)	(0.0517)	(0.0535)	(0.0541)	(0.0541)
Observations	13,620	13,620	13,620	13,620	13,620
Number of municipalities	1,135	1,135	1,135	1,135	1,135
Geographical Controls	No	Yes	Yes	Yes	Yes
Initial Conditions	No	No	Yes	Yes	Yes
Temperature	No	No	No	Yes	Yes
Control Variables	No	No	No	No	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3 with the inclusion of different control variables. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables is the natural logarithm of the total credit in each municipality. All regressions include municipality and year fixed effects. The sample is the 1,135 municipalities in Brazilian Semiarid region.

Table A.2 – Question 1: Effects on Credit by sectors

	(1) Credit	(2) Agriculture	(3) Manufacturing	(4) Livestock	(5) Services	(6) Trade
High Exposure x (Year= 2006)	-0.1666**	-0.7721***	-0.4803*	-0.0360	-1.5386***	0.1018
	(0.0693)	(0.2649)	(0.2864)	(0.0821)	(0.3010)	(0.3417)
High Exposure x (Year= 2007)	-0.1254	-0.1458	-0.7490**	-0.0255	-1.2326***	-0.6309*
	(0.0793)	(0.2574)	(0.2933)	(0.0906)	(0.3070)	(0.3224)
High Exposure x (Year= 2008)	0.0827	0.1673	-0.1457	0.1880*	-0.8155***	-0.1226
	(0.1014)	(0.2570)	(0.2921)	(0.1118)	(0.2968)	(0.3164)
High Exposure x (Year= 2009)	0.0373	0.3101	0.0188	0.0573	-0.5405*	0.3574
	(0.0793)	(0.2090)	(0.2841)	(0.0905)	(0.3004)	(0.3110)
High Exposure x (Year= 2010)	0.0148	0.1716	0.1857	-0.0107	-0.1079	-0.0710
	(0.0437)	(0.1924)	(0.2908)	(0.0564)	(0.2921)	(0.2959)
High Exposure x (Year= 2012)	-0.1179**	0.4049*	-0.1931	-0.0788	-0.5024	-0.2380
	(0.0463)	(0.2064)	(0.2851)	(0.0507)	(0.3084)	(0.2728)
High Exposure x (Year= 2013)	-0.1499***	0.0813	-0.3593	-0.1263**	-0.1585	-0.0092
	(0.0500)	(0.2266)	(0.3013)	(0.0559)	(0.3153)	(0.2943)
High Exposure x (Year= 2014)	-0.2434***	-0.1121	0.2217	-0.2048***	-0.5416*	-0.2336
	(0.0488)	(0.2385)	(0.2950)	(0.0562)	(0.3209)	(0.3191)
High Exposure x (Year= 2015)	-0.2668***	0.0101	0.2758	-0.1543**	-0.2893	-0.7111**
	(0.0530)	(0.2396)	(0.2975)	(0.0640)	(0.3252)	(0.3128)
High Exposure x (Year= 2016)	-0.2729***	0.3078	-0.1260	-0.2314***	-0.4074	-0.5588*
	(0.0532)	(0.2417)	(0.2883)	(0.0613)	(0.3209)	(0.3344)
High Exposure x (Year= 2017)	-0.3123***	-0.1596	-0.4669	-0.2412***	-0.2780	-0.6943**
	(0.0535)	(0.2392)	(0.3039)	(0.0568)	(0.3381)	(0.3207)
Observations	13,620	13,620	13,620	13,620	13,620	13,620
Number of municipalities	1,135	1,135	1,135	1,135	1,135	1,135
Geographical Controls	No	No	No	No	No	No
Initial Conditions	No	No	No	No	No	No
Temperature	No	No	No	No	No	No
Control Variables	No	No	No	No	No	No
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the natural logarithm of the total credit, agriculture credit, manufacturing credit, livestock credit, services credit and trade credit in each municipality. All regressions include municipality and year fixed effects. The sample is the 1,135 municipalities in Brazilian Semiarid region.

Table A.3 – Question 1: Effects on Delinquency Rates

	(1) Delinquency	(2) Delinquency	(3) Delinquency	(4) Delinquency	(5) Delinquency
High Exposure x (Year= 2006)	-0.0041	0.0023	0.0020	0.0017	-0.0016
	(0.0068)	(0.0068)	(0.0067)	(0.0068)	(0.0070)
High Exposure x (Year= 2007)	-0.0233***	-0.0203***	-0.0205***	-0.0207***	-0.0225***
	(0.0070)	(0.0070)	(0.0070)	(0.0070)	(0.0072)
High Exposure x (Year= 2008)	-0.0327***	-0.0279***	-0.0279***	-0.0279***	-0.0281***
	(0.0067)	(0.0063)	(0.0064)	(0.0064)	(0.0066)
High Exposure x (Year= 2009)	-0.0245***	-0.0187***	-0.0187***	-0.0186***	-0.0178***
	(0.0054)	(0.0052)	(0.0052)	(0.0052)	(0.0053)
High Exposure x (Year= 2010)	-0.0128***	-0.0097***	-0.0097***	-0.0094**	-0.0092**
	(0.0037)	(0.0037)	(0.0038)	(0.0038)	(0.0039)
High Exposure x (Year= 2012)	0.0083**	0.0113***	0.0114***	0.0120***	0.0102***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0034)
High Exposure x (Year= 2013)	0.0155***	0.0182***	0.0185***	0.0192***	0.0165***
	(0.0046)	(0.0047)	(0.0045)	(0.0045)	(0.0046)
High Exposure x (Year= 2014)	0.0130***	0.0172***	0.0175***	0.0180***	0.0160***
	(0.0046)	(0.0047)	(0.0046)	(0.0046)	(0.0046)
High Exposure x (Year= 2015)	0.0135**	0.0191***	0.0194***	0.0206***	0.0166***
	(0.0056)	(0.0057)	(0.0055)	(0.0055)	(0.0056)
High Exposure x (Year= 2016)	0.0178***	0.0259***	0.0262***	0.0271***	0.0234***
	(0.0059)	(0.0058)	(0.0057)	(0.0057)	(0.0058)
High Exposure x (Year= 2017)	0.0177***	0.0272***	0.0275***	0.0282***	0.0240***
	(0.0064)	(0.0063)	(0.0061)	(0.0061)	(0.0063)
Observations	13,620	13,620	13,620	13,620	13,620
Number of municipalities	1,135	1,135	1,135	1,135	1,135
Geographical Controls	No	Yes	Yes	Yes	Yes
Initial Conditions	No	No	Yes	Yes	Yes
Temperature	No	No	No	Yes	Yes
Control Variables	No	No	No	No	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3 with the inclusion of different control variables. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables is the natural logarithm of the delinquency rates in each municipality. All regressions include municipality and year fixed effects. The sample is the 1,135 municipalities in Brazilian Semiarid region.

Table A.4 – Question 1: Effects on GDP

	(1) GDP	(2) GDP	(3) GDP	(4) GDP	(5) GDP
High Exposure x (Year= 2006)	-0.0004	0.0180*	0.0180*	0.0178*	0.0041
	(0.0096)	(0.0095)	(0.0093)	(0.0092)	(0.0091)
High Exposure x (Year= 2007)	0.0055	0.0260***	0.0293***	0.0291***	0.0222**
	(0.0094)	(0.0095)	(0.0091)	(0.0091)	(0.0091)
High Exposure x (Year= 2008)	0.0160**	0.0279***	0.0331***	0.0331***	0.0244***
	(0.0080)	(0.0081)	(0.0077)	(0.0077)	(0.0078)
High Exposure x (Year= 2009)	-0.0215***	-0.0134*	-0.0038	-0.0037	-0.0058
	(0.0074)	(0.0075)	(0.0070)	(0.0070)	(0.0070)
High Exposure x (Year= 2010)	0.0017	0.0113*	0.0077	0.0081	0.0065
	(0.0065)	(0.0068)	(0.0064)	(0.0066)	(0.0064)
High Exposure x (Year= 2012)	-0.0169*	-0.0089	-0.0098	-0.0093	-0.0053
	(0.0090)	(0.0095)	(0.0091)	(0.0091)	(0.0090)
High Exposure x (Year= 2013)	-0.0194*	-0.0106	-0.0064	-0.0057	0.0009
	(0.0108)	(0.0124)	(0.0099)	(0.0098)	(0.0094)
High Exposure x (Year= 2014)	-0.0135	-0.0160*	-0.0141	-0.0136	-0.0071
	(0.0088)	(0.0092)	(0.0088)	(0.0089)	(0.0093)
High Exposure x (Year= 2015)	-0.0233**	-0.0223**	-0.0173*	-0.0162	-0.0084
	(0.0097)	(0.0102)	(0.0096)	(0.0099)	(0.0101)
High Exposure x (Year= 2016)	-0.0324***	-0.0353***	-0.0270**	-0.0261**	-0.0169
	(0.0121)	(0.0129)	(0.0122)	(0.0126)	(0.0131)
High Exposure x (Year= 2017)	-0.0185	-0.0244*	-0.0162	-0.0153	-0.0081
	(0.0138)	(0.0143)	(0.0145)	(0.0148)	(0.0160)
Observations	13,620	13,620	13,620	13,620	13,620
Number of municipalities	1,135	1,135	1,135	1,135	1,135
Geographical Controls	No	Yes	Yes	Yes	Yes
Initial Conditions	No	No	Yes	Yes	Yes
Temperature	No	No	No	Yes	Yes
Control Variables	No	No	No	No	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3 with the inclusion of different control variables. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the natural logarithm of GDP in each municipality. All regressions include municipality and year fixed effects. The sample is the 1,135 municipalities in Brazilian Semiarid region.

Table A.5 – Question 1: Effects on GDP by sector

	(1) GDP	(2) Agriculture	(3) Services	(4) Manufacturing	(5) Public Adm
High Exposure x (Year= 2006)	-0.0004	0.0201	-0.0313**	-0.0131	-0.0154**
	(0.0096)	(0.0225)	(0.0126)	(0.0262)	(0.0071)
High Exposure x (Year= 2007)	0.0055	0.0716***	-0.0262**	0.0690**	-0.0249***
	(0.0094)	(0.0257)	(0.0116)	(0.0271)	(0.0047)
High Exposure x (Year= 2008)	0.0160**	0.0829***	-0.0338***	0.1742***	-0.0025
	(0.0080)	(0.0217)	(0.0109)	(0.0340)	(0.0044)
High Exposure x (Year= 2009)	-0.0215***	-0.0014	-0.0414***	0.0577**	-0.0099***
	(0.0074)	(0.0186)	(0.0098)	(0.0263)	(0.0036)
High Exposure x (Year= 2010)	0.0017	0.0204	0.0028	0.0083	-0.0041*
	(0.0065)	(0.0194)	(0.0079)	(0.0189)	(0.0023)
High Exposure x (Year= 2012)	-0.0169*	0.0418*	-0.0243***	-0.0435**	-0.0106***
	(0.0090)	(0.0223)	(0.0068)	(0.0171)	(0.0023)
High Exposure x (Year= 2013)	-0.0194*	0.0758***	-0.0049	-0.0057	-0.0130***
	(0.0108)	(0.0240)	(0.0076)	(0.0253)	(0.0031)
High Exposure x (Year= 2014)	-0.0135	0.0999***	-0.0147	-0.0338	-0.0053
	(0.0088)	(0.0242)	(0.0097)	(0.0282)	(0.0035)
High Exposure x (Year= 2015)	-0.0233**	0.0208	-0.0027	-0.0790**	0.0011
	(0.0097)	(0.0270)	(0.0101)	(0.0311)	(0.0039)
High Exposure x (Year= 2016)	-0.0324***	0.0291	-0.0169	-0.0828**	-0.0050
	(0.0121)	(0.0275)	(0.0117)	(0.0373)	(0.0044)
High Exposure x (Year= 2017)	-0.0185	0.0290	0.0043	-0.0759*	-0.0031
	(0.0138)	(0.0274)	(0.0133)	(0.0425)	(0.0046)
Observations	13,620	13,620	13,620	13,620	13,620
Number of municipalities	1,135	1,135	1,135	1,135	1,135
Geographical Controls	No	No	No	No	No
Initial Conditions	No	No	No	No	No
Temperature	No	No	No	No	No
Control Variables	No	No	No	No	No
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the natural logarithm of total GDP, Agriculture GDP, Services GDP, Manufacturing GDP, and Public Administration GDP in each municipality. All regressions include municipality and year fixed effects. The sample is the 1,135 municipalities in Brazilian Semiarid region.

Table A.6 – Question 1: Effects on Jobs

	(1) Jobs	(2) Jobs	(3) Jobs	(4) Jobs	(5) Jobs
High Exposure x (Year= 2006)	-0.0268	-0.0164	-0.0335	-0.0335	-0.0585*
	(0.0264)	(0.0295)	(0.0306)	(0.0306)	(0.0314)
High Exposure x (Year= 2007)	-0.0144	-0.0031	-0.0145	-0.0145	-0.0396
	(0.0252)	(0.0283)	(0.0286)	(0.0286)	(0.0300)
High Exposure x (Year= 2008)	-0.0204	-0.0122	-0.0226	-0.0226	-0.0359
	(0.0267)	(0.0305)	(0.0305)	(0.0305)	(0.0311)
High Exposure x (Year= 2009)	0.0351	0.0416	0.0416	0.0416	0.0302
	(0.0230)	(0.0260)	(0.0257)	(0.0257)	(0.0252)
High Exposure x (Year= 2010)	0.0280	0.0369	0.0246	0.0246	0.0167
	(0.0261)	(0.0306)	(0.0273)	(0.0274)	(0.0270)
High Exposure x (Year= 2012)	-0.0143	-0.0202	-0.0195	-0.0195	-0.0171
	(0.0200)	(0.0215)	(0.0210)	(0.0210)	(0.0208)
High Exposure x (Year= 2013)	-0.0211	-0.0281	-0.0265	-0.0265	-0.0202
	(0.0261)	(0.0287)	(0.0283)	(0.0283)	(0.0300)
High Exposure x (Year= 2014)	0.0049	-0.0047	-0.0103	-0.0103	-0.0110
	(0.0253)	(0.0287)	(0.0272)	(0.0273)	(0.0286)
High Exposure x (Year= 2015)	-0.0074	-0.0207	-0.0118	-0.0119	-0.0023
	(0.0214)	(0.0230)	(0.0233)	(0.0234)	(0.0241)
High Exposure x (Year= 2016)	0.0158	0.0034	0.0057	0.0057	0.0148
	(0.0267)	(0.0303)	(0.0296)	(0.0297)	(0.0299)
High Exposure x (Year= 2017)	-0.0093	-0.0241	-0.0115	-0.0115	0.0017
	(0.0241)	(0.0272)	(0.0269)	(0.0271)	(0.0275)
Observations	13,620	13,620	13,620	13,620	13,620
Number of municipalities	1,135	1,135	1,135	1,135	1,135
Geographical Controls	No	Yes	Yes	Yes	Yes
Initial Conditions	No	No	Yes	Yes	Yes
Temperature	No	No	No	Yes	Yes
Control Variables	No	No	No	No	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3 with the inclusion of different control variables. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables is the natural logarithm of total Jobs in each municipality. All regressions include municipality and year fixed effects. The sample are the 1,135 municipalities in Brazilian Semiarid region.

Table A.7 – Question 1: Effects on Jobs by sector

	(1) Jobs	(2) Agriculture	(3) Manufacturing	(4) Services	(5) Trade	(6) Public Adm
High Exposure x (Year= 2006)	-0.0268	-0.0323	-0.0978	0.1158***	-0.0258	-0.0407
	(0.0264)	(0.0502)	(0.0605)	(0.0436)	(0.0339)	(0.0496)
High Exposure x (Year= 2007)	-0.0144	-0.0004	-0.0528	0.0814**	-0.0584*	-0.0168
	(0.0252)	(0.0452)	(0.0581)	(0.0390)	(0.0306)	(0.0460)
High Exposure x (Year= 2008)	-0.0204	0.0134	-0.0564	0.0549	-0.0390	-0.0279
	(0.0267)	(0.0410)	(0.0522)	(0.0373)	(0.0294)	(0.0461)
High Exposure x (Year= 2009)	0.0351	0.0005	-0.0718	0.0369	-0.0658***	0.0983**
	(0.0230)	(0.0364)	(0.0485)	(0.0325)	(0.0251)	(0.0441)
High Exposure x (Year= 2010)	0.0280	0.0219	-0.0541	0.0385	-0.0329	0.0692
	(0.0261)	(0.0314)	(0.0401)	(0.0296)	(0.0211)	(0.0475)
High Exposure x (Year= 2012)	-0.0143	0.0002	0.0407	0.0362	0.0051	-0.0120
	(0.0200)	(0.0296)	(0.0407)	(0.0243)	(0.0207)	(0.0402)
High Exposure x (Year= 2013)	-0.0211	0.0148	0.1460***	0.0413	0.0230	-0.2625*
	(0.0261)	(0.0414)	(0.0549)	(0.0332)	(0.0256)	(0.1384)
High Exposure x (Year= 2014)	0.0049	-0.0136	0.0722	0.0077	-0.0250	0.0114
	(0.0253)	(0.0394)	(0.0569)	(0.0379)	(0.0258)	(0.0487)
High Exposure x (Year= 2015)	-0.0074	-0.0510	0.0700	0.0093	0.0119	-0.0163
	(0.0214)	(0.0436)	(0.0554)	(0.0367)	(0.0254)	(0.0451)
High Exposure x (Year= 2016)	0.0158	-0.0191	0.1040*	0.0366	-0.0031	0.0179
	(0.0267)	(0.0437)	(0.0595)	(0.0404)	(0.0267)	(0.0574)
High Exposure x (Year= 2017)	-0.0093	-0.0156	0.0893	0.0346	-0.0073	-0.0730
	(0.0241)	(0.0486)	(0.0614)	(0.0376)	(0.0286)	(0.0953)
Observations	13,620	13,620	13,620	13,620	13,620	13,620
Number of municipalities	1,135	1,135	1,135	1,135	1,135	1,135
Geographical Controls	No	No	No	No	No	No
Initial Conditions	No	No	No	No	No	No
Temperature	No	No	No	No	No	No
Control Variables	No	No	No	No	No	No
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the natural logarithm of total Jobs, Agriculture Jobs, Manufacturing Jobs, Services Jobs, Trade Jobs, and Public Administration Jobs in each municipality. All regressions include municipality and year fixed effects. All regressions include municipality and year fixed effects. The sample is the 1,135 municipalities in Brazilian Semiarid region.

APPENDIX B: Question 2: Dynamic Difference-in-Differences Analysis

Table B.1 – Question 2: Effects on Credit

	(1) Credit	(2) Credit	(3) Credit	(4) Credit	(5) Credit
Inside x (Year= 2006)	0.2258*	0.2308*	0.1664	0.1659	0.1643
	(0.1279)	(0.1275)	(0.1134)	(0.1129)	(0.1097)
Inside x (Year= 2007)	0.1371	0.1374	0.1162	0.1157	0.0995
	(0.1589)	(0.1547)	(0.1541)	(0.1541)	(0.1491)
Inside x (Year= 2008)	0.1494	0.1521	0.1139	0.1176	0.1203
	(0.1500)	(0.1465)	(0.1423)	(0.1421)	(0.1380)
Inside x (Year= 2009)	0.1785	0.1811	0.1577	0.1594	0.1564
	(0.1394)	(0.1379)	(0.1348)	(0.1346)	(0.1317)
Inside x (Year= 2010)	0.1285	0.1230	0.1199	0.1295	0.1320
	(0.0839)	(0.0832)	(0.0839)	(0.0837)	(0.0838)
Inside x (Year= 2012)	0.2963***	0.2818***	0.2744***	0.2799***	0.2778***
	(0.0885)	(0.0884)	(0.0885)	(0.0879)	(0.0860)
Inside x (Year= 2013)	0.1499*	0.1423*	0.1450*	0.1452*	0.1581*
	(0.0831)	(0.0835)	(0.0833)	(0.0830)	(0.0825)
Inside x (Year= 2014)	0.0897	0.0808	0.0968	0.1000	0.1039
	(0.0986)	(0.0994)	(0.0993)	(0.0989)	(0.0981)
Inside x (Year= 2015)	-0.0062	-0.0120	-0.0009	0.0045	0.0307
	(0.0966)	(0.0975)	(0.0981)	(0.0975)	(0.0936)
Inside x (Year= 2016)	0.1394	0.1325	0.1463	0.1447	0.1575
	(0.0993)	(0.0995)	(0.1007)	(0.1006)	(0.0987)
Inside x (Year= 2017)	0.0911	0.0839	0.0904	0.0883	0.1094
	(0.0976)	(0.0978)	(0.1017)	(0.1025)	(0.0985)
Observations	5,160	5,160	5,160	5,160	5,160
Number of municipalities	430	430	430	430	430
Geographical Controls	No	Yes	Yes	Yes	Yes
Initial Conditions	No	No	Yes	Yes	Yes
Temperature	No	No	No	Yes	Yes
Control Variables	No	No	No	No	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3 with the inclusion of different control variables. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables is the natural logarithm of the total credit in each municipality. All regressions include municipality and year fixed effects. The sample is the 430 municipalities at the border of the semiarid.

Table B.2 – Question 2: Effects on Credit by sectors

	(1) Credit	(2) Agriculture	(3) Manufacturing	(4) Livestock	(5) Services	(6) Trade
Inside x (Year= 2006)	0.2258*	0.3268	0.5142	0.1530	0.4309	0.4490
	(0.1279)	(0.4122)	(0.4815)	(0.1676)	(0.5033)	(0.5461)
Inside x (Year= 2007)	0.1371	-0.0377	0.0958	0.2668	0.7075	0.5566
	(0.1589)	(0.3540)	(0.4746)	(0.1920)	(0.4873)	(0.5206)
Inside x (Year= 2008)	0.1494	0.3189	-0.0251	0.1750	0.5472	0.5189
	(0.1500)	(0.3497)	(0.5000)	(0.2012)	(0.4663)	(0.5041)
Inside x (Year= 2009)	0.1785	0.3241	0.1063	0.0052	1.0209**	0.7776*
	(0.1394)	(0.3115)	(0.4691)	(0.1911)	(0.4786)	(0.4568)
Inside x (Year= 2010)	0.1285	-0.0246	0.0647	0.1470	0.5020	0.2129
	(0.0839)	(0.2750)	(0.4770)	(0.1179)	(0.4147)	(0.4666)
Inside x (Year= 2012)	0.2963***	-0.1746	0.0631	0.3698***	0.8001*	0.5226
	(0.0885)	(0.2960)	(0.4792)	(0.1096)	(0.4769)	(0.4650)
Inside x (Year= 2013)	0.1499*	0.3455	0.3464	0.0808	0.6477	0.1421
	(0.0831)	(0.2872)	(0.4666)	(0.1164)	(0.4997)	(0.5089)
Inside x (Year= 2014)	0.0897	0.0157	0.3363	0.0105	0.7554	0.7702
	(0.0986)	(0.3337)	(0.4861)	(0.1109)	(0.5024)	(0.5360)
Inside x (Year= 2015)	-0.0062	0.4016	0.0440	0.0685	0.2462	0.5038
	(0.0966)	(0.3090)	(0.4702)	(0.1422)	(0.5112)	(0.5545)
Inside x (Year= 2016)	0.1394	0.1661	0.2349	0.1685	0.5781	0.5754
	(0.0993)	(0.3328)	(0.5230)	(0.1217)	(0.4759)	(0.5593)
Inside x (Year= 2017)	0.0911	0.0551	0.5085	0.2754**	0.6470	0.5187
	(0.0976)	(0.3276)	(0.5190)	(0.1181)	(0.4990)	(0.5210)
Observations	5,160	5,160	5,160	5,160	5,160	5,160
Number of municipalities	430	430	430	430	430	430
Geographical Controls	No	No	No	No	No	No
Initial Conditions	No	No	No	No	No	No
Temperature	No	No	No	No	No	No
Control Variables	No	No	No	No	No	No
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the natural logarithm of the total credit, agriculture credit, manufacturing credit, livestock credit, services credit, and trade credit in each municipality. All regressions include municipality and year fixed effects. The sample is the 430 municipalities at the border of the semiarid.

Table B.3 – Question 2: Effects on Delinquency Rates

	(1) Delinquency	(2) Delinquency	(3) Delinquency	(4) Delinquency	(5) Delinquency
Inside x (Year= 2006)	-0.0022	-0.0012	0.0012	0.0012	-0.0011
	(0.0118)	(0.0116)	(0.0115)	(0.0115)	(0.0115)
Inside x (Year= 2007)	-0.0040	-0.0029	-0.0029	-0.0028	-0.0031
	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0116)
Inside x (Year= 2008)	-0.0029	-0.0004	0.0001	0.0000	0.0008
	(0.0108)	(0.0104)	(0.0104)	(0.0104)	(0.0103)
Inside x (Year= 2009)	-0.0055	-0.0039	-0.0038	-0.0039	-0.0036
	(0.0085)	(0.0084)	(0.0084)	(0.0084)	(0.0082)
Inside x (Year= 2010)	-0.0077	-0.0063	-0.0063	-0.0066	-0.0061
	(0.0061)	(0.0059)	(0.0059)	(0.0059)	(0.0057)
Inside x (Year= 2012)	-0.0059	-0.0054	-0.0057	-0.0059	-0.0062
	(0.0060)	(0.0058)	(0.0058)	(0.0058)	(0.0058)
Inside x (Year= 2013)	-0.0032	-0.0033	-0.0042	-0.0042	-0.0056
	(0.0083)	(0.0081)	(0.0079)	(0.0079)	(0.0079)
Inside x (Year= 2014)	-0.0275***	-0.0259***	-0.0268***	-0.0269***	-0.0276***
	(0.0081)	(0.0079)	(0.0077)	(0.0077)	(0.0077)
Inside x (Year= 2015)	-0.0253***	-0.0244***	-0.0254***	-0.0256***	-0.0272***
	(0.0094)	(0.0092)	(0.0091)	(0.0091)	(0.0088)
Inside x (Year= 2016)	-0.0067	-0.0066	-0.0076	-0.0075	-0.0099
	(0.0100)	(0.0099)	(0.0098)	(0.0098)	(0.0095)
Inside x (Year= 2017)	0.0042	0.0037	0.0026	0.0027	-0.0004
	(0.0108)	(0.0108)	(0.0106)	(0.0107)	(0.0103)
Observations	5,160	5,160	5,160	5,160	5,160
Number of municipalities	430	430	430	430	430
Geographical Controls	No	Yes	Yes	Yes	Yes
Initial Conditions	No	No	Yes	Yes	Yes
Temperature	No	No	No	Yes	Yes
Control Variables	No	No	No	No	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3 with the inclusion of different control variables. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables is the natural logarithm of the delinquency rates in each municipality. All regressions include municipality and year fixed effects. The sample is the 430 municipalities at the border of the semiarid.

Table B.4 – Question 2: Effects on GDP

	(1) GDP	(2) GDP	(3) GDP	(4) GDP	(5) GDP
Inside x (Year= 2006)	0.0215	0.0282*	0.0280*	0.0281*	0.0262
	(0.0180)	(0.0167)	(0.0168)	(0.0168)	(0.0164)
Inside x (Year= 2007)	0.0257	0.0318**	0.0313**	0.0314**	0.0284*
	(0.0168)	(0.0158)	(0.0158)	(0.0158)	(0.0154)
Inside x (Year= 2008)	0.0248*	0.0273*	0.0269*	0.0267*	0.0235*
	(0.0147)	(0.0144)	(0.0145)	(0.0144)	(0.0140)
Inside x (Year= 2009)	0.0194	0.0217*	0.0204	0.0204	0.0185
	(0.0130)	(0.0128)	(0.0126)	(0.0126)	(0.0126)
Inside x (Year= 2010)	0.0034	0.0061	0.0061	0.0056	0.0046
	(0.0106)	(0.0100)	(0.0101)	(0.0103)	(0.0103)
Inside x (Year= 2012)	-0.0260	-0.0241	-0.0244	-0.0247	-0.0267
	(0.0191)	(0.0184)	(0.0188)	(0.0187)	(0.0193)
Inside x (Year= 2013)	-0.0290	-0.0265	-0.0272	-0.0272	-0.0325
	(0.0247)	(0.0243)	(0.0249)	(0.0249)	(0.0248)
Inside x (Year= 2014)	-0.0104	-0.0128	-0.0127	-0.0128	-0.0167
	(0.0141)	(0.0139)	(0.0140)	(0.0140)	(0.0142)
Inside x (Year= 2015)	-0.0080	-0.0094	-0.0101	-0.0104	-0.0130
	(0.0207)	(0.0207)	(0.0207)	(0.0208)	(0.0210)
Inside x (Year= 2016)	-0.0043	-0.0046	-0.0059	-0.0058	-0.0117
	(0.0280)	(0.0278)	(0.0277)	(0.0277)	(0.0277)
Inside x (Year= 2017)	0.0283	0.0235	0.0221	0.0222	0.0167
	(0.0287)	(0.0280)	(0.0279)	(0.0278)	(0.0278)
Observations	5,160	5,160	5,160	5,160	5,160
Number of municipalities	430	430	430	430	430
Geographical Controls	No	Yes	Yes	Yes	Yes
Initial Conditions	No	No	Yes	Yes	Yes
Temperature	No	No	No	Yes	Yes
Control Variables	No	No	No	No	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3 with the inclusion of different control variables. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the natural logarithm of GDP in each municipality. All regressions include municipality and year fixed effects. The sample is the 430 municipalities at the border of the semiarid.

Table B.5 – Question 2: Effects on GDP by sector

	(1) GDP	(2) Agriculture	(3) Services	(4) Manufacturing	(5) Public Adm
Inside x (Year= 2006)	0.0215	-0.0474	0.0222	0.0938**	0.0118
	(0.0180)	(0.0367)	(0.0198)	(0.0436)	(0.0110)
Inside x (Year= 2007)	0.0257	-0.0297	0.0269	0.0779*	0.0051
	(0.0168)	(0.0374)	(0.0171)	(0.0446)	(0.0080)
Inside x (Year= 2008)	0.0248*	0.0013	0.0141	0.0227	0.0081
	(0.0147)	(0.0318)	(0.0157)	(0.0598)	(0.0076)
Inside x (Year= 2009)	0.0194	-0.0163	0.0116	0.0620	0.0036
	(0.0130)	(0.0285)	(0.0144)	(0.0399)	(0.0058)
Inside x (Year= 2010)	0.0034	-0.0264	0.0048	0.0158	0.0020
	(0.0106)	(0.0262)	(0.0108)	(0.0254)	(0.0041)
Inside x (Year= 2012)	-0.0260	-0.0414	-0.0047	0.0158	0.0007
	(0.0191)	(0.0379)	(0.0096)	(0.0245)	(0.0038)
Inside x (Year= 2013)	-0.0290	0.0063	-0.0056	-0.0098	-0.0006
	(0.0247)	(0.0359)	(0.0122)	(0.0388)	(0.0054)
Inside x (Year= 2014)	-0.0104	-0.0012	-0.0075	-0.0065	-0.0033
	(0.0141)	(0.0363)	(0.0164)	(0.0394)	(0.0058)
Inside x (Year= 2015)	-0.0080	-0.0411	-0.0127	0.0081	-0.0037
	(0.0207)	(0.0407)	(0.0201)	(0.0562)	(0.0070)
Inside x (Year= 2016)	-0.0043	-0.0834*	-0.0145	0.0669	-0.0048
	(0.0280)	(0.0460)	(0.0257)	(0.0691)	(0.0077)
Inside x (Year= 2017)	0.0283	0.0025	0.0237	0.1062	-0.0006
	(0.0287)	(0.0522)	(0.0266)	(0.0728)	(0.0080)
Observations	5,160	5,160	5,160	5,160	5,160
Number of municipalities	430	430	430	430	430
Geographical Controls	No	No	No	No	No
Initial Conditions	No	No	No	No	No
Temperature	No	No	No	No	No
Control Variables	No	No	No	No	No
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the natural logarithm of total GDP, Agriculture GDP, Services GDP, Manufacturing GDP, and Public Administration GDP in each municipality. All regressions include municipality and year fixed effects. The sample is the 430 municipalities at the border of the semiarid.

Table B.6 – Question 2: Effects on Jobs

	(1) Jobs	(2) Jobs	(3) Jobs	(4) Jobs	(5) Jobs
Inside x (Year= 2006)	0.0204	0.0259	0.0259	0.0261	0.0207
	(0.0380)	(0.0372)	(0.0372)	(0.0372)	(0.0365)
Inside x (Year= 2007)	0.0036	0.0090	0.0087	0.0088	0.0048
	(0.0352)	(0.0346)	(0.0346)	(0.0346)	(0.0341)
Inside x (Year= 2008)	0.0204	0.0253	0.0252	0.0249	0.0234
	(0.0347)	(0.0343)	(0.0345)	(0.0345)	(0.0355)
Inside x (Year= 2009)	0.0262	0.0296	0.0296	0.0295	0.0267
	(0.0338)	(0.0338)	(0.0340)	(0.0339)	(0.0342)
Inside x (Year= 2010)	0.0316	0.0333	0.0335	0.0328	0.0293
	(0.0314)	(0.0316)	(0.0318)	(0.0318)	(0.0323)
Inside x (Year= 2012)	0.0246	0.0225	0.0219	0.0214	0.0173
	(0.0256)	(0.0251)	(0.0253)	(0.0253)	(0.0261)
Inside x (Year= 2013)	0.0282	0.0252	0.0246	0.0246	0.0165
	(0.0377)	(0.0380)	(0.0381)	(0.0381)	(0.0372)
Inside x (Year= 2014)	0.0081	0.0061	0.0058	0.0056	-0.0003
	(0.0339)	(0.0334)	(0.0334)	(0.0335)	(0.0340)
Inside x (Year= 2015)	0.0274	0.0244	0.0239	0.0234	0.0157
	(0.0360)	(0.0361)	(0.0363)	(0.0363)	(0.0366)
Inside x (Year= 2016)	0.0426	0.0397	0.0392	0.0393	0.0341
	(0.0379)	(0.0378)	(0.0379)	(0.0379)	(0.0389)
Inside x (Year= 2017)	0.0139	0.0114	0.0104	0.0106	0.0070
	(0.0359)	(0.0355)	(0.0353)	(0.0353)	(0.0356)
Observations	5,160	5,160	5,160	5,160	5,160
Number of municipalities	430	430	430	430	430
Geographical Controls	No	Yes	Yes	Yes	Yes
Initial Conditions	No	No	Yes	Yes	Yes
Temperature	No	No	No	Yes	Yes
Control Variables	No	No	No	No	Yes
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3 with the inclusion of different control variables. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables is the natural logarithm of total Jobs in each municipality. The sample is the 430 municipalities at the border of the semiarid.

Table B.7 – Question 2: Effects on Jobs by sector

	(1) Jobs	(2) Agriculture	(3) Manufacturing	(4) Services	(5) Trade	(6) Public Adm
Inside x (Year= 2006)	0.0204	0.0163	0.0878	0.2057***	0.0315	0.0509
	(0.0380)	(0.0904)	(0.1069)	(0.0705)	(0.0518)	(0.0703)
Inside x (Year= 2007)	0.0036	0.0335	0.0642	0.0610	0.0368	0.0653
	(0.0352)	(0.0802)	(0.0986)	(0.0612)	(0.0465)	(0.0742)
Inside x (Year= 2008)	0.0204	0.1320*	0.0693	0.0677	0.0843*	0.1062
	(0.0347)	(0.0679)	(0.0867)	(0.0584)	(0.0469)	(0.0793)
Inside x (Year= 2009)	0.0262	0.1031	0.0258	0.0652	0.0246	0.0185
	(0.0338)	(0.0641)	(0.0772)	(0.0543)	(0.0379)	(0.0771)
Inside x (Year= 2010)	0.0316	0.0233	0.0362	-0.0141	0.0264	0.0872
	(0.0314)	(0.0474)	(0.0638)	(0.0415)	(0.0279)	(0.0735)
Inside x (Year= 2012)	0.0246	-0.0142	0.0735	0.0126	0.0311	0.0229
	(0.0256)	(0.0484)	(0.0719)	(0.0361)	(0.0267)	(0.0737)
Inside x (Year= 2013)	0.0282	-0.0754	-0.0336	-0.0047	0.0331	-0.0587
	(0.0377)	(0.0607)	(0.0931)	(0.0518)	(0.0338)	(0.2315)
Inside x (Year= 2014)	0.0081	0.0422	-0.0547	0.0701	0.0303	-0.0098
	(0.0339)	(0.0616)	(0.0919)	(0.0575)	(0.0330)	(0.0760)
Inside x (Year= 2015)	0.0274	0.1164	0.0477	0.0117	0.0246	0.0300
	(0.0360)	(0.0721)	(0.0932)	(0.0584)	(0.0372)	(0.0857)
Inside x (Year= 2016)	0.0426	0.1272*	0.1478	0.0408	0.0056	0.0266
	(0.0379)	(0.0697)	(0.1038)	(0.0620)	(0.0400)	(0.0910)
Inside x (Year= 2017)	0.0139	0.1110	0.2295**	-0.0363	-0.0230	-0.0241
	(0.0359)	(0.0756)	(0.1074)	(0.0605)	(0.0418)	(0.1607)
Observations	5,160	5,160	5,160	5,160	5,160	5,160
Number of municipalities	430	430	430	430	430	430
Geographical Controls	No	No	No	No	No	No
Initial Conditions	No	No	No	No	No	No
Temperature	No	No	No	No	No	No
Control Variables	No	No	No	No	No	No
Municipality & Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of estimating the Equation 3. Robust standard errors (in parentheses) are clustered at the municipal level. The observation unit is a municipality-year. The regressions are for 12 years (from 2006 to 2017). Significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the natural logarithm of total Jobs, Agriculture Jobs, Manufacturing Jobs, Services Jobs, Trade Jobs, and Public Administration Jobs in each municipality. All regressions include municipality and year fixed effects. The sample is the 430 municipalities at the border of the semiarid.