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BARREN LIVES: DROUGHT SHOCKS AND AGRICULTURAL VULNERABILITY IN THE BRAZILIAN SEMI-ARID

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Barren Lives: drought shocks and agricultural vulnerability in the Brazilian Semi-Arid

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ABSTRACT

This paper studies the effects of drought shocks in a vulnerable environment – the Brazilian Semi-Arid. We analyze the impact of drought shocks, measured as deviations from historical averages, on agricultural outcomes and land-use decisions in a region that suffers recurrently with drought. After controlling for municipality and year fixed effects, we use weather shocks to exactly identify outcomes. Our benchmark results show substantial effects on the loss of crop area and on the value of agricultural output. By investigating distributional effects, we are able to show that crops related to family farming suffer more from drought shocks. We follow our investigation by testing heterogeneity effects and show that adequate water provision and maintenance of forest cover help in reducing the impact of drought shocks. Finally, we show that drought shocks in the previous year affect deforestation in the following year.

JEL Classification: Q15, Q54.

Keywords: Drought, Climate Change, Agricultural Output; Brazilian Semi-Arid.

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1 Introduction

It is widely recognized that there is an anthropogenic contribution to the observed changes in climate. According to statements held by IPCC reports, the agreement among the scientific community has grown stronger regarding the effects of human-based emissions on the accumulation of carbon dioxide in the atmosphere The effects of climate change are not only felt with temperature extremes. Besides temperature changes, one expects precipitation changes, humidity changes, changes in the frequency and intensity of tropical cyclones, sea-level rise, ocean acidification, effects on droughts and floods and huge impacts on ecosystems, with loss of biodiversity (Hsiang and Kopp, 2018).

As regards droughts, climate change is expected to alter frequency and intensity, since temperature and precipitation changes affect moisture conditions. Indeed, dry regions are expected to suffer more with an increase in the frequency of droughts (Collins et al., 2013), as can already be noticed in the Brazilian Semi-Arid (Brito et al., 2018). As long as these regions tend to have lower agricultural productivity and need more investments in adaptation, the effects of climate change may be especially severe.

This paper analyzes the impact of drought shocks, measured as deviations from historical averages, on agricultural outcomes and land-use decisions in a region that suffers recurrently with drought. The Brazilian Semiarid is the driest and poorest region in the country. The region has a total area of 1.13 million km^2, covering parts of 9 states in Brazil. Total population living within the Semiarid is 27.5 million, nearly 13% of the country's total population and income per capita is 42% of the Brazilian average (Medeiros et al., 2012; Silva et al., 2016).[1]

We investigate how large deviations from historical averages in rainfall averages patterns affect the area of harvest, production and productivity. To identify causal effects, we use longitudinal data on Brazilian semi-arid municipalities from 2006 to 2017. After controlling for municipality and year fixed effects, we use weather shocks - rainfall idiosyncratic shocks in our case - to exactly identify outcomes. As argued by Dell et al. (2014), there is a growing body of the literature that uses weather shocks to exactly identify outcomes, under the assumption that weather shocks occur randomly in time.[2]

Our benchmark results show substantial effects on the loss of crop area and on the value

[1] As the last demographic census was carried out in 2010 and the new delimitation of the Brazilian Semi-Arid was in 2017, some demographic data may be out of date. Therefore, in addition to the references cited, some updated data can be found at the following link: http://www.sudene.gov.br/images/arquivos/semiarido/arquivos/Rela%C3%A7%C3%A3o_de_Munic%C3%ADpios_Semi%C3%A1rido.pdf

[2] Blanc and Schlenker (2017) provide a discussion on the use of panel models in assessments of climate impacts on agriculture.

of agricultural output: a rainfall deviation of one standard deviation from the historical average is related to a loss of 3.4% of crop area and 18.4% of output. When we consider non-linear effects, results are more striking. A year of extreme drought, defined as a dummy when rainfall deviation is two standard deviations less than the historical average, leads to a loss of 5.3%-5.9% in crop area and 26%-32% in the value of output.

As investments in adaptation can reduce the impact of those shocks, we focus on the effects across different crops. Credit and insurance markets imperfections result in underinvestment in adaptation. This is especially important for family farms, which suffer more from liquidity contraints. In this context, we show that outcomes from crops related to family farming - beans and corn - are those suffering from drought shocks - as highlighted by Cirino et al. (2015), whereas business crops, such as sugarcane and coffee, have small effects. Unfortunately, the harsh effects on family farming cannot be qualified as surprising. As of 1946, De Castro (1952) had already mapped this pattern in the Brazilian Semiarid.

In order to better understand, mechanisms, we follow our investigation by testing heterogeneity effects. We show that adequate water provision and maintenance of forest cover help in reducing the impact of drought shocks in our measures of agriculture outcome. Finally, we test whether drought shocks in the previous year affect deforestation in the following year. The intuition behind this test rests on the historical pattern of slash and burn agricultural in Brazil. We consider these to be the main contributions of this paper, since the extensive literature on drought shocks in the Brazilian semiarid region has already detailed this phenomenon - as detailed in Section III -, but slight effort has been made to quantify the heterogeneous effects of drought shocks on the agricultural output in this region.

To further increase confidence in our results, we conduct a placebo test, by estimating the effects of previous and forward drought shocks on our main dependent variables. Moreover, it is important to account for spatial and temporal dependence in climatic exposure. Then, we correct standard errors for spatial dependence using the procedure proposed by Conley (1999) and results are robust to this correction.

This paper contributes to the literature pioneered by Deschênes and Greenstone (2007), which uses random fluctuations in weather to assess agricultural impacts of climate change. Given the greater importance of agriculture and higher levels of poverty, developing countries are much more vulnerable to these weather shocks on the welfare of its population. Burgess et al. (2017), for instance, assess the effects of high temperatures in mortality in rural India. According to the authors, potential mechanisms relate to lower productivity and wages in seasons with extreme hot days. Taraz (2017) also investigates the effects of climate change on India‘s farmers. However, the author focuses on adaptation efforts and shows that adaptation only recovers a fraction of lost profits. We contribute to this literature by providing a specific focus on droughts shocks, instead of temperature, in a developing country with a significant agricultural production, as it is Brazil.[3]

We also contribute to the literature that discusses the importance of natural resources to stabilize effects from drought shocks. Wani et al. (2012) discuss how watershed management in dryland tropics increases net returns from crop production, while conserving the natural resource base. In a paper similar to ours in its conclusions, Noack et al. (2019) relate droughts to negative shocks in crop incomes, which are, nevertheless, partly offset by forest extraction. In addition, the authors show that more biodiversity reduces the effects of droughts. We show that tree cover attenuates the effects of droughts, as well. Moreover, our results also imply an increase in the intensity of natural resources use after a year of drought, which is a mechanism diverse from the one found by Noack et al. (2019).

Our results show how the impacts of droughts in dryland regions can be substantial. Morover, we are able to show that the adequate provision of public goods, represented by water supply and native vegetation, can have important effects in reducing the damage extension of drought shocks.

In the next section, we review and contextualize our object of study, highlighting the historical background of drought in the Brazilian Semi-Arid and reviewing the literature on climate shocks in this region. In Section III, we describe the database that we set up for this paper. In Section IV, we explain the empirical strategy used. Section V presents the results proposed in this paper. Finally, a brief section presents the main conclusions of this study.

2 Background

2.1 Historical Background

The Portuguese occupation of the Brazilian territory in colonial times was concentrated in the fertile coastal areas of the Atlantic Forest biome. In the Northeast, sugarcane plantations led to a very profitable trade to local landowners and the Portuguese crown, but extremely unequal due to their dependence on slave labour, captured mostly from Africa but also from the indigenous native population. In order to supply beef products to the coastal population, extensive cattle ranching occupied the interior lands of the Northeast (Prado Jr, 2017; Furtado, 2005).

[3] Assunção and Chein (2016) use a mix of Ricardian and production function approaches to simulate the effects of climate change on agricultural productivity in Brazil. Average effects are expected to decrease yields by 18%, with a significant variation.

Due to low fertility and water scarcity, there was little interest in developing plantations in the Northeast semiarid. Therefore, cultivation in these interior lands was mainly carried out by subsistence farmers, mixing the remnants of the native indigenous population with impoverished European descendants and freed or escaped former slaves. Corn and beans have been the most important crops since these colonial times, even though other cultivation products were also important, mainly manioc (Prado Jr, 2017; De Castro, 1952).

The rare settlements and villages that catered to merchants, cattle ranchers, and travelers subsisted on groundwater and subsistence agriculture. Over time, the extensive nature of the occupation and the long distances to the dynamic centers of the economy have deteriorated the average yield of semi-arid production (Furtado, 2005).

The decline of sugarcane plantations since the mid-seventeenth century and demographic expansion in the coastal areas resulted in a process of migration of the population towards the semiarid region. However, in spite of occasional booms of demand for ranching products, especially during the "cattle cycle" in the XVIII century, the semi-arid region remained characterized by high levels of poverty, unemployment and critical dependence on subsistence cultivation (Furtado, 2005; Ab'Sáber, 1999).

The low development of the region if compared to other parts of Brazil has always been associated to the climate conditions of the drylands, characterized by very low levels of precipitation and recurrent severe drought events. Under favorable conditions, the Brazilian semi-arid is one of the semi-arid regions of the planet most favorable to occupation, in terms of water availability and food (De Castro, 1952). However, the frequent repetition of severe droughts led to extreme events, resulting in food insecurity, poverty and migration towards other parts of Brazil. But climatic conditions are not the only cause for the social vulnerability in the region: the concentration of economic and political power in the hands of the large landowners (locally known as "coronels"), a large portion of landless and jobless population and the deficit of public policies aiming the access to water resources and the agrarian issue, maintains a vicious cycle of poverty and social vulnerability, and the region remains as the poorest part in Brazil (Ab'Sáber, 1999).[4]

2.2 Recent Background

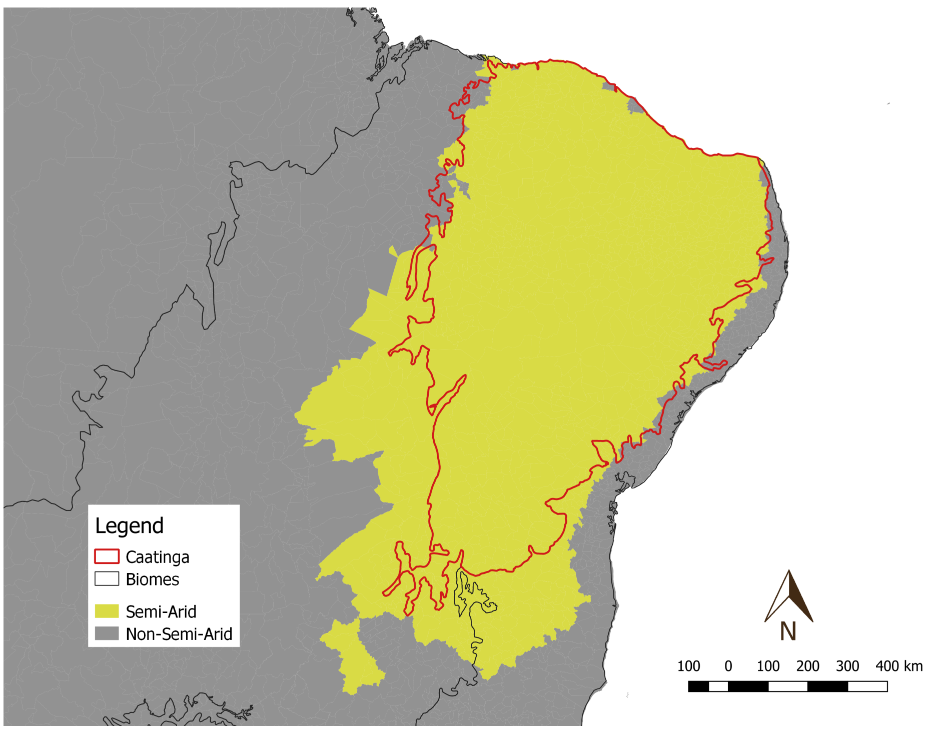
The Brazilian Semi-Arid region occupies most of the interior land of the Northeast region. In ecological and biodiversity terms, the Brazilian Semi-Arid is closely related to the Caatinga, which had its flora adapted to the dry and hot climate that lasts for almost the

[4]For an analysis of the political effects of this process, see Leal (2012).

whole year. Thus, climatic conditions constituted the only biome that is located exclusively in Brazilian territory (Ab'Sáber, 1999).

The Brazilian Institute of Geography and Statistics (IBGE) and the Northeast Development Superintendence (SUDENE) define the Brazilian Semi-Arid region based on specific technical criteria of very low precipitation (less than 800 mm/year on average) and/or high daily water deficit of over 60% [5] (Medeiros et al., 2012). Figure 1 shows the 1.13 million square kilometers area covered by the 1,262 municipalities classified as in the Semi-Arid region.

Figure 1: Semi-Arid Region and Caatinga Biome



Notes: Own elaboration

The Brazilian Semi-Arid is the largest semiarid territory in the world. It is also the semi-arid region with the largest human population: 27.5 million people, or around 13% of the Brazilian population, according to the Brazilian Demographic Census of 2010, most of them living in rural areas and in municipalities with less than 50,000 inhabitants (Medeiros et al., 2012).

Most of the agricultural production in the region comes from family farming, either for subsistence or for commercialization. These farmers have little investment capacity and

[5] Evapotranspiration exceeds 60% of precipitation every day of the year

Table 1: Family and Non-Family Crop Patterns in Brazil

Crop	Family Farming Area (ha)	Non-Family Farming Area (ha)	Total Farming Area (ha)	Share of Family Farming Area	Share of Each Crop on Sum of Crops Area
			Semi-Arid		
Rice	136,055	33,075	169,130	80.4%	2.5%
Bean	2,436,941	317,758	2,754,699	88.5%	41.5%
Cassava	334,074	48,269	382,343	87.4%	5.8%
Corn	2,329,061	457,872	2,786,933	83.6%	41.9%
Soy	707	456,850	457,557	0.2%	6.9%
Coffee Bean	39,696	53,748	93,444	42.5%	1.4%
Total	**5,276,534**	**1,367,572**	**6,644,106**	**79.4%**	**100.0%**
			Non-Semi-Arid		
Rice	1,028,437	1,190,471	2,218,908	46.3%	6.6%
Bean	952,465	442,162	1,394,627	68.3%	4.1%
Cassava	1,138,825	181,085	1,319,910	86.3%	3.9%
Corn	4,003,675	4,800,206	8,803,881	45.5%	26.1%
Soy	2,697,533	14,499,204	17,196,737	15.7%	50.9%
Wheat	319,515	951,467	1,270,982	25.1%	3.8%
Coffee Bean	726,736	855,193	1,581,929	45.9%	4.7%
Total	**10,867,186**	**22,919,788**	**33,786,974**	**32.2%**	**100.0%**

Note: Own elaboration using data from the 2006 IBGE Agricultural Census

low resilience to the increasingly frequent drought events, leading to high social vulnerability and major food and economic insecurity during these extreme events (De Castro, 1952; Travassos et al., 2013; Silvia et al., 2013)

Table 1 compares output data, disaggregated in terms of family and non-family farming and specific crops, for semiarid land and the rest of the country. It is evident that family farming is far more important in cultivation in the semiarid region than in the rest of the country, and that corn and beans are responsible for 83% of the family farming area in the Brazilian Semi-Arid.

The historical vulnerability and poverty of the semi-arid population has caught attention from policymakers since Brazilian independence. The perceptions on how to proceed, however, vary widely, usually between two extremes (Campos, 2015):

- Man-made interventions, such as reservoirs and other civil engineering works, can provide a technically and economically feasible solution to reduce water scarcity;

- Droughts are an inevitable problem caused by climatic conditions, but the social vulnerability in the region is a consequence of the inadequate productive and social structure to this unavoidable natural phenomenon.

The creation of the National Department of Works against Drought (DNOCS in its Portuguese acronym) in 1909, aiming at the construction of cisterns, reservoirs and other hydrological infrastructure, has been for a long time associated with the view that proper engineering would be enough to solve the water problem. The most recent example of this perception is the construction of the Transposition of São Francisco River Project, initiated in the mid-2000s and yet to be concluded. This ambitious project aims at the construction of more than 700 km of channels in order to assure the availability of water, in 2025, to nearly 12 million inhabitants of cities in the Brazilian Semi-Arid.

However, critics of this view argue that these infrastructure projects have high financial costs but little efficacy to solve the problems (Cirilo, 2008).[6] The creation of the Superintendency for the Development of the Northeast (SUDENE) in 1959, was originally intended to undertake the structural changes in the productive system in the region, with the support of many fiscal and credit incentives. Nevertheless, this approach has also failed. Celso Furtado, the man who idealized the creation of SUDENE, recognized the incapacity to surpass the archaic but well-established political structures that impeded the process of transformation in the semi-arid, including the unequal distribution of land and other resources (Furtado, 1989).

As a consequence, despite these initiatives, problems related to droughts and food security are still very relevant in the region. The El Niño phenomenon, which tends to increase temperature and decrease precipitation in the Brazilian sem-arid region, still generates large losses in agricultural productivity (Cirino et al., 2015). In turn, the extensive and unsustainable occupation of the semiarid region is further compromising its lands, generating a phenomenon known as desertification, which decreases its humidity and productivity (Cirilo, 2008; Travassos et al., 2013; Vieira et al., 2015).[7]

In 2011 one of the most severe and disastrous droughts in recent decades in the region began, causing severe social damage and huge agricultural losses (Marengo et al., 2016;

[6] Indeed, there is an ongoing problem with the overuse of groundwater for irrigation that is affecting the supply of water to the São Francisco river. Part of the problem is related to the absence of a fee on water use. See: https://www1.folha.uol.com.br/mercado/2020/01/agricultura-irrigada-gera-disputa-por-agua-na-bahia.shtml

[7] Droughts are also associated with increased child mortality and various problems in pregnancy (Rocha and Soares, 2015).

Brito et al., 2018; Cunha et al., 2019). As highlighted by Gutiérrez et al. (2014), despite the public policies implemented in the last decade, it seems that there are very important structural deficits to mitigate disaster damage, such as this latest drought, but also to prevent the occurrence of long-term disasters. Therefore, in addition to the historical deficiencies and vulnerabilities, the increased frequency, duration and severity of droughts due to climate change – as described by Brito et al. (2018) – will build a new scenario, yet its roots are already known. Hence, it is essential to understand which factors are capable of mitigating the damages in the region and guaranteeing food security for the semiarid population in a context where climate change might bring increasing challenges to the region.

3 Data

3.1 Independent Variables

Our goal is to assess the effects of drought on Brazilian semi-arid agriculture and test whether municipality-specific structures reflect heterogeneous drought resilience. Thus, we collected several independent variables that can be divided into two groups: (i) climate variations, which identify years of drought event; (ii) and structural variables as land use type and type of access to water, which can capture heterogeneous effects on agriculture.

To identify drought events, we use the database *Terrestrial Air Temperature and Terrestrial Rainfall: 1990-2017 Monthly Monthly Grid Series, Version 5.01* (Matsuura and Willmott, 2018). This database presents monthly data of georeferenced temperatures and precipitation - by 0.5x0.5 degree grids - between 1900 and 2017. First, we aggregate the monthly data into a per year one and, as Rocha and Soares (2015), build a continuous variable of annual precipitation deviation from the historical average of each grid, according to the following equation:

$$Rainfall\ deviation_{gt} = \frac{mean\left(P_{g1900-2017}\right) - P_{gt}}{sd\left(P_{ig1900-2017}\right)}$$

Where $Rainfall\ deviation_{gt}$ is the deviation of annual precipitation from the historical average for each grid g and year t. Since temperature can be an important control for our model, we calculate the same metric for temperature. To merge these variables with the municipalities, we have identified the closest grid to each municipality, using the centroids for both municipalities and grids. Also, considering the exogeneity of grids, we can correct problems of spatial correlation of precipitation and temperature variables (Burgess et al., 2018).

One problem with using a continuous variable to identify an extreme event is that drought-related losses may be not linearly correlated with rainfall (for example, decreasing rainfall from 80mm to 60mm may not have the same effect as dropping from 50mm to 30mm, although the difference between the lower and upper values is identical). Therefore, we also have built two dummy variables to identify drought events, according to the following principles:

$$\begin{cases} \text{if } 0 < Rainfall\ deviation_{mt} < 1, \text{ then } Drought = 1; \\ \text{if } Rainfall\ deviation_{mt} \geq 1, \text{ then } Extreme\ Drought = 1. \end{cases}$$

The first set of structural variables, chosen to identify the heterogeneous resilience of municipalities, are the types of access to water in rural households, available in *Table 1395 - 2010 Brazilian Demographic Census* (IBGE, 2010). From these databases, it was possible to identify how many rural households per municipality had, in 2010, as main source of water the (i) general supply network, (ii) wells or springs within property or village, (iii) wells or spring outside property or village, (iv) rivers, lakes or streams, or (v) water truck and rainwater. For practical purposes, we chose to use the percentage of water access type as:

$$TH_{ma2010} = \frac{H_{ma2010}}{H_{m2010}}$$

Where TH_{ma2010} is the percentage of rural households in municipality m with type of access to water a. H_{ma2010} is the number of rural households in m with access to water a in 2010, while H_{m2010} is the total number of rural households in municipality m in 2010.

It is also an important matter for this paper to study whether conserving vegetation increases agricultural resilience to droughts and to understand the dynamics of deforestation following drought events. Therefore, we set up an annual forest stock variable from the MapBiomas platform data, which, through Google Earth Engine, assembles annual historical series of georeferenced land use data for the entire Brazilian territory. [8] We have calculated the percentage of forest stock according to the equation:

$$TF_{mt} = \frac{F_{mt}}{Total\ Area_m}$$

[8] We have selected the land use categories 1 to 9 to forest stock, according the Mapbiomas codes. To measure the forest losses, we considered the transition of categories 1-9 to categories 14-21, 24, 30.

Where TF_{mt} is the forest area rate in municipality m in year t, F_{mt} is the area of forest stock, and $Total\ Area_m$ is the area occupied by municipality m. Similarly, we set up a $ForestLoss_{mt}$ variable from the same land use database.

3.2 Dependent Variables

To measure the direct and heterogeneous effects of drought on agriculture, we collected data on agricultural production from *Table 5457 - Brazilian Municipal Agricultural Research* (SIDRA/IBGE). The variables used for the purpose of this study were: Planted Area and Harvested Area, in hectares, Average Productivity, in kilograms per hectare harvested, and Value of Agricultural Production, in currency units (R$). All these variables are available at the municipal and year level, by crop type. It is particularly interesting to observe the heterogeneity of results by crop type, since crops such as corn and beans are more associated with family production and have a large weight in the total planted area of the Brazilian semiarid (IBGE, 2006).

By subtracting the variables Planted Area and Harvested Area, we can calculate a measure of Lost Area. This new Lost Area variable is convenient for this study, since, to evaluate drought losses, it is convenient to compare a counterfactual - Planted Area - in relation to an observed output - Harvested Area. Therefore, the calculation of the Lost Area is given by the following equation:

$$TLA_{mtc} = \frac{CA_{mtc} - HA_{mtc}}{CA_{mtc}}$$

Where TLA_{mtc} is the percentage of area that was cultivated but not harvested from crop c in municipality m and year t. We also performed tests for the Value of Agricultural Production, in order to give robustness to our tests. However, this variable may suffer from relative price fluctuations of crop types that do not have relationship with our mesaure of drought shocks (under the assumption that landholders are price takers). Thus, we also assess the effects on the productivity per hectare harvested, which allows a complementary analysis, measuring whether there are losses within the harvested areas, in adition to the loss of the cultivated areas.

3.3 Descriptive Statistics

Our sample is a balanced panel that comprises the 1,262 municipalities within the Brazilian Semi-Arid. Considering the 12 years of the panel, we have a total of 15,144 observations.

Table 2 summarizes our main descriptive statistics. The average municipality has a lost area of 13.8% yearly. This an extensive area and much higher than the rest of the country, which loses on average 1.2% of planted area each year. As expected, drought is also important to the municipalities in our sample: the average rainfall deviation is 0.92. In addition, 45.1% of the municipalities in an year suffer from droughts and 15.6% from extreme droughts.

Table 2: Summary Statistics: yearly muncipality data 2006-2017, Brazilian Semi-Arid

Variables	Mean	Std. deviation	Min	Max	Number of observations
Lost Area	13.847	25.045	0	100	15,128
Ln (Output)	7.825	1.872	0	14.394	15,143
Rainfall Deviation	0.120	0.920	-3.435	2.342	15,144
(Dummy of) Drought	0.451	0.497	0	1	15,144
(Dummy of) Extreme Drought	0.156	0.362	0	1	15,144
Forest	0.543	0.250	0.007	.993	15,144
Temperature deviation	1.034	1.121	-1.949	4.939	15,144

Note: Yearly observations by municipality, from 2006 to 2017. Data originally from: (i) IBGE;(ii) the Terrestrial Air Temperature and Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series, Version 5.01; (iii) Mapbiomas.

4 Empirical Strategy

We expect that a drought shock, as defined in the previous section, might have a negative effect on variables related to agricultural production. For identification, we rely on the data panel structure, which allows us to control unobservable variables from municipalities and common annual shocks, including municipality and year fixed effects. Therefore, our benchmark model to be estimated is:

$$Y_{it} = \beta_0 + \beta_1 Drought\ Shock_{it} + \gamma X_{it} + \alpha_t + \lambda_i + \varepsilon_{it} \ (6)$$

Where Y_{it} is a variable that measures agricultural loss. Throughout the paper, we are going to use: (i) lost area; (ii) output value and (iii) crop yields, as our main dependent variables. The coefficient - β_1 - is our coefficient of interest and measures the average treatment effect in municipalities within the Brazilian Semi-Arid. X_{it} is a vector of covariates that might also affect agricultural losses, as temperature deviations from historical averages. The term α_t is a time fixed effect, which captures yearly shocks common to all municipalities, λ_i is the municipality fixed effect, which captures effects of unobservable and invariant variables in time. The model error term is ε_{it}. In alternative specifications, we also allow for municipality-specific time trends.

Our key identifying assumption relies on the hypothesis that drought shocks, defined as annual rainfall deviations from historical averages (from 1900 to 2017), are uncorrelated with other determinants of agricultural production, conditional on municipality and year fixed-effects. In order to establish a causal relationship between drought shocks and agricultural outcomes, we need to take into account the possible omitted variable bias that can arise from variables that over time are correlated with drought and agricultural results. As the region is inherently dry, it is plausible that individuals already adapt to local dryness. That is why we scale by standard deviation, which means that we are looking to intense variations in proportion to the municipalities'usual variation. Moreover, we include controls for time-varying factos that could affect agricultural outcomes as well, such as temperature deviations from historical averages. As it is not possible to control for all unobservable time-varying factors, we conduct some robustness checks and placebo tests, which are discussed in the next section.

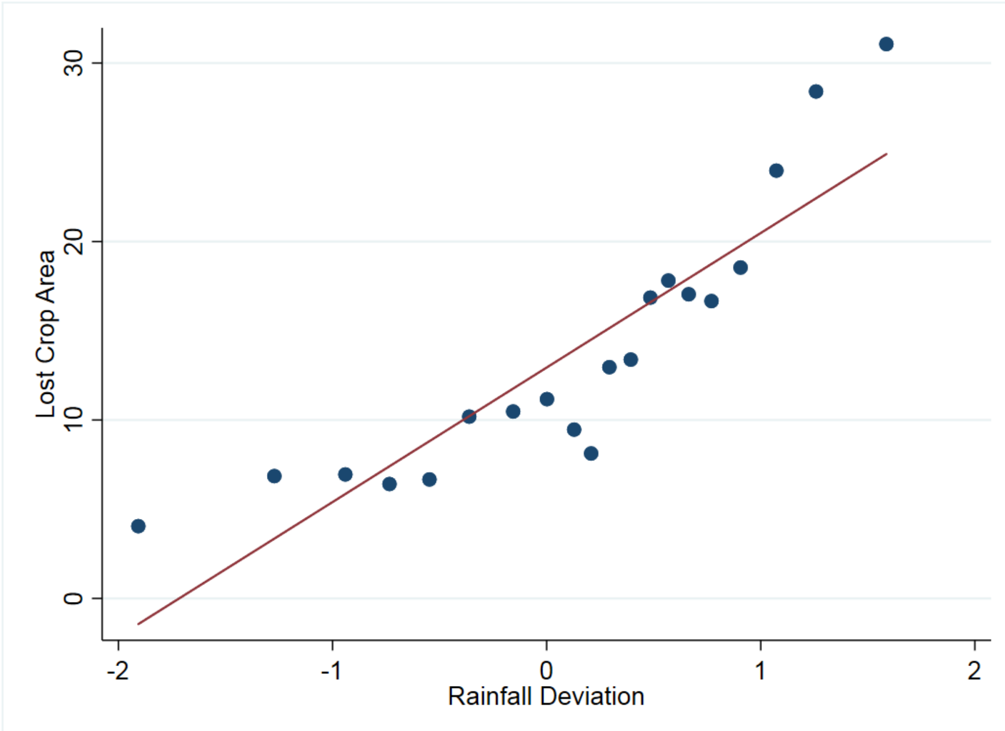
Moreover, the variable $Drought\ Shock_{it}$ potentially has spatial correlation problems since it is originally at the grid level and we calculate the nearest grid to each municipality's centroid to attribute municipal data. In this case, the attribution of values by municipality is clustered. Therefore, standard errors must be adjusted, even when the estimate considers fixed-effects (Abadie et al., 2017). Indeed, it is important to account for spatial and temporal dependence in climatic exposure (Hsiang, 2016). In order to account for this potential bias, we make use of two different strategies: (i) robust standard errors are clustered at the pixel level, since the interpolation necessarily leads to spatial dependence; and (ii) we apply "Conley" spatial standard errors (Conley, 1999).

5 Results

5.1 Main results

This section presents the main results of this paper. To anticipate part of the discussion, Figure 2 displays a binned scatterplot generated by regressing rainfall deviation and the total cropped area lost. Municipality fixed-effects are also included. The figure demonstrats that, on average, municipalities affected with rainfall deviation higher than average have higher cropped area lost, on average. Further, as we can check by a visual inspection of the figure, it appears that there is a non-linear relationship for extreme values of drought (Rainfall Deviation greater than historical average for more than one standard deviation). Therefore, this is an important feature to be tested as well in our main results.

Figure 2: Scatter Plot of Residual Rainfall Deviation and Lost Crop Area



Notes: The figure above depicts the relationship between residual Lost Crop Area and residual Rainfall Deviation, controlling for municipality fixed-effects. Each observation on the plot is averaged over twenty equal-sized bins.

In Table 3, we report our baseline results of the relationship between drought and agricultural output. In Columns (1) and (2), we report the corelation between rainfall deviation - a continuous measure of drought - and the total annual crop area that was lost, using Pooled OLS estimation. From Column (1), a one standard deviation increase in drought in relation to the historical average is associated with a loss of 6.1% of loss in cropped area, which is 44% of the dependent variables mean. In Column (2), we control for temperature deviation. Results are similar and slightly lower, which is suggestive of no strong correlation between temperature and rainfall deviation.

In Columns (3) and (4) of Table 3, we include municipality and year fixed effects. The panel structure of the data allows us to control for unobsorvable time-invariant heterogeneity that could be correlated with our measure of drought shock. Moreover, the inclusion of year fixed effects in Column (4) controls for common shocks that might affect every municipalities each year. In this context, the inclusion of year fixed effects is important since it controls for climate shocks that might not be heterogeneous in space and other factors such as the conditions of farm-credit that can vary on an annual basis. The estimated coefficient with the addition of municipality fixed effects is even larger - 7.76. However, the inclusion of year fixed effect reduces the estimated coefficient to 3.38, which is suggestive of important yearly effects on the loss of cropped area.

As it appears from Figure 2, it seems that there is a non-linear relationship as rainfall deviation achieves higher values. To test this hypothesis, Columns (5) and (6) includes dummy variables for years with high and extreme drought. We define a variable *Drought* as a dummy with value equal to 1 if the variable Rainfall Deviation is between 0 and 1. That is to say, if, in a given pair municipality x year, rainfall is less than historical average for up to one standard deviation, the variable *Drought* equals one. Similarly, we define *Extreme Drought* as deviations from historical average above one standard deviation. In Column (6), we add specific municipality trends, in order to account for specific unobserved factors varying in time. The results from Columns (5) and (6) are suggestive of a non-linear relationship, where extreme drought appear to have an important effect in the loss of agricultural area. Compared to years without drought, an year with moderate drought has 3.2% more of lost area and years with extreme drought have 5.9% more lost area. In addition, the estimated coefficient for *Extreme Drought* is 87% larger than the estimated coefficient for *Drought*.

Table 3: Pooled OLS and Fixed Effect Models of Drought Shocks Impact on Lost of Crop Area

VARIABLES	(1) Lost Crop Area	(2) Lost Crop Area	(3) Lost Crop Area	(4) Lost Crop Area	(5) Lost Crop Area	(6) Lost Crop Area
Rainfall deviation	6.133***	5.962***	7.769***	3.381***		
	(0.477)	(0.580)	(0.575)	(0.639)		
Dummy of Drought					3.843***	3.205***
					(0.881)	(0.928)
Dummy of Extreme Drought					5.312***	5.998***
					(1.644)	(1.557)
Temperature Deviation		0.273	-0.379	-1.656***	-1.358***	-1.825***
		(0.523)	(0.493)	(0.539)	(0.520)	(0.527)
Observations	15,128	15,128	15,128	15,128	15,128	15,128
R-squared	0.051	0.051	0.352	0.405	0.404	0.515
Municipality FE	N	N	Y	Y	Y	Y
Year FE	N	N	N	Y	Y	Y
Municipality Trend	N	N	N	N	N	Y
Cluster	Grid	Grid	Grid	Grid	Grid	Grid
Number of municipalities	1262	1262	1262	1262	1262	1262
Number of clusters	359	359	359	359	359	359
Mean of dependent variable	13.85	13.85	13.85	13.85	13.85	13.85

Note: Robust standard errors are clustered by grids. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

In Table 3, we analyzed the effects on the loss of cropped area caused by droughts. However, it is also interesting to understand what happens to agricultural output, which is what ultimately translates into farm income.

In this sense, Table 4 displays results for the effects of drought shocks on the value of agriculturual output. Column (1) presents the fixed effects model, adding temperature deviation as a covariate. The estimated coefficient implies a sizable effect on agricultural output: an year with rainfall less than historical average of one standard deviation implies a reduction in the value of agricultural output of 16.5%. When we add municipality specific time trends, as in Column (2), the effect is even larger: 18.4%. Columns (3) and (4) explore possible non-linear effects in agricultural output. Moderate drought, as our definition, implies a loss of agriculture output between 17.3% and 20.4%, according with the econometric specification. Extreme drought implies, as expected, higher losses, ranging from 25.8% to 32.4%. That is, a municipality that suffers with extreme drought is expected to lose between one quarter and one third of the value of agriculture output.

Table 4: Fixed Effect Models of Drought Shock Impact on Agricultural Output

VARIABLES	(1) Ln(Output)	(2) Ln(Output)	(3) Ln(Output)	(4) Ln(Output)
Rainfall deviation	-0.165***	-0.184***		
	(0.026)	(0.025)		
Dummy of Drought			-0.204***	-0.173***
			(0.036)	(0.041)
Dummy of Extreme Drought			-0.258***	-0.324***
			(0.060)	(0.066)
Observations	15,143	15,143	15,143	15,143
R-squared	0.831	0.879	0.830	0.878
Municipality FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Municipality Trend	N	Y	N	Y
Controls	Y	Y	Y	Y
Cluster	Grid	Grid	Grid	Grid
Number of municipalities	1262	1262	1262	1262
Number of clusters	359	359	359	359
Mean of dependent variable	7.825	7.825	7.825	7.825

Note: Robust standard errors are clustered by grids. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

It should be noted that the distributional effects of agricultural losses from droughts can be quite important, since it is probable that these effects are conditoned on the capacity to make investments in adaptation. This hypothesis will be investigated in the following subsections.

5.2 Effects on different crops as a proxy for distributive effects

As previously discussed, the Brazilian Semi-Arid has an important share of family farming in the total share of agricultural activities. The main crops cultivated by families in the Semi-Arid are corn and beans, whereas business farm especialize in the production of sugarcane and, to some extent, coffee. Thus, based on this division of labor, we estimate the effects of drought shocks on different crops as a way to infer the distributional impacts. Table 5 displays the effects, by crop, on lost area and productivity, as measured by the natural logarithm of each crop specific yield. On Panel A, we present the effects on lost area, by crops. On columns (1) and (2), we evaluate the effects on crops, which tend to be cultivated by families - beans and corns. These crops suffer the most when there is a drought: a year with rainfall one standard deviation below its historical average implies a loss of 5% in cropped area with beans and 6.3% in cropped area with corn. Columns (3) and (4) measure the effects on the loss of area on two crops more associated to business farm - sugarcane and coffee. There is no sizable effect associated to rainfall deviation on lost area for those crops.

When one evaluates the effects on crop yields, the impact is more widespread. Results on Panel B show negative effects on yields for the four crops evaluated. However, the effects are stronger for beans and corns - which lose, respectively, 12% and 21.2% of its yields - than for sugarcane and coffee, which lose 4.8% and 11.4% of its respective yields. Therefore, aside from important effects for the agricultural sector, drought shocks have negative distributive consequences, as well.[9]

[9] Assunção and Chein (2016) discuss the impact of climate change on agricultural productivity and rural poverty.

Table 5: Effects of Drought Shocks on Different Crops

	(1) Beans	(2) Corn	(3) Sugarcane	(4) Coffee
	Panel B: Effects on Lost Area			
Rainfall deviation	5.003***	6.383***	-0.209	1.877
	(0.783)	(0.889)	(0.286)	(1.145)
Observations	14,772	14,720	6,363	2,317
R-squared	0.520	0.519	0.393	0.310
Mean of dependent variable	16.21	19.64	1.615	1.659
	Panel A: Effects on Yield			
Rainfall deviation	-0.120***	-0.212***	-0.048***	-0.114***
	(0.027)	(0.030)	(0.015)	(0.027)
Observations	14,236	13,718	6,352	2,298
R-squared	0.596	0.619	0.652	0.809
Number of municipalities	1260	1260	644	234
Number of clusters	359	359	270	111
Municipality FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Municipality Trend	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Cluster	Grid	Grid	Grid	Grid

Note: Robust standard errors are clustered by grids. Significance: *** p<0.01, ** p<0.05, * p<0.1.

5.3 Heterogeneity

The results outlined so forth highlight the need to understand how the characteristics of the municipalities might affect agricultural output. As previously discussed, drought shocks might have a heterogeneous impact on agricultural output to the level of investment in adaptation led by each municipality. Therefore, in this section, we examine heterogeneity in the treatment effects, since landholders and local governments can decide to invest in adapation such as water availability and forest cover.[10]

Table 6 displays heterogeneous effects based on the provision of a fundamental public good: water. The table is divided in two panels. Panel A displays the effects on the loss of

[10]Forest cover can act as a buffer to drought shocks, which protects groundwater or intensifies the hydrological cycle, reducing the high evapotranspiration characteristic of these regions, besides acting as a filter, improving the quality of both groundwater and surface water (Ellison et al., 2017; Lopes et al., 2019).

crop area and Panel B displays the effects on the value of agricultural output. Each column presents heterogeneous effects according to the municipal level of provision of water from distinct infrastructure levels. Column (1) presents the effects of rainfall deviation and how it interacts with a network of rural water supply. In relation to lost area, the estimated coefficient of the interaction is negative, albeit not statistically robust. As regards the value of agricultural output (Panel B), the coefficient of the interaction is positive. Taken together, it implies that the provision of a network of water supply has an effect of protecting producers from losing output.

Results from Columns (2) and (3) provide a similar interpretation: having wells to collect water - independently if being within property - also provide protection against drought shocks. From Column (2), a back of the envelope calculation implies that a drought with rainfall deviation equal to one standard deviation below historical average and one-third of properties having wells within property, lost area would be zero, instead of 5.4% in the case where zero properties have wells.

Columns (4) and (5) dispay heterogeneous effects of more vulnerable methods of gathering water: collecting it from a river or counting on rainfall to have water. In municipalities where these methods are predominant, the effects of drought shocks are magnified, with more lost area and output. These results reinforce the discussion from the previous subsection, which infers that drought shocks have negative distributive effects. From Table 6, we can see that more vulnerable municipalities, as measured by the provision of a fundamental public good - network of water supply - suffer the most with drought.

Table 6: Heterogeneity Effects - Water Supply

	(1)	(2)	(3)	(4)	(5)
	Panel A - Dep. Var: Lost Area				
Rainfall deviation	4.198***	5.386***	4.915***	2.647***	0.397
	(0.852)	(0.710)	(0.771)	(0.729)	(0.684)
Rainfall deviation x Rural Water Supply	-2.706				
	(1.710)				
Rainfall deviation x Well water within property		-16.419***			
		(2.206)			
Rainfall deviation x Well water outside property			-9.905***		
			(2.215)		
Rainfall deviation x Water supply in river				6.708***	
				(2.576)	
Rainfall deviation x Water supplied by rain					10.790***
					(1.940)
	Panel B - Dep. Var: Ln(Output)				
Rainfall deviation	-0.245***	-0.230***	-0.237***	-0.122***	-0.005
	(0.034)	(0.029)	(0.031)	(0.028)	(0.027)
Rainfall deviation x Rural Water Supply	0.265***				
	(0.060)				
Rainfall deviation x Well water within property		0.537***			
		(0.091)			
Rainfall deviation x Well water outside property			0.466***		
			(0.095)		
Rainfall deviation x Water supply in river				-0.386***	
				(0.110)	
Rainfall deviation x Water supplied by rain					-0.579***
					(0.070)
Observations	15,128	15,128	15,128	15,128	15,128
Municipality FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Cluster	Grid	Grid	Grid	Grid	Grid
Number of municipalities	1262	1262	1262	1262	1262
Number of clusters	359	359	359	359	359

Note: Robust standard errors are clustered by grids. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Another possible investment in adaptation is the maintenance of forest cover, since it represents an important factor in maintaining water supply even in dry environments (Ellison et al., 2012; Ilstedt et al., 2016).[11] In this context, the maintenance of tree cover can be seen as an investment in adaptation, meanwhile it reduces farming area. Thus, Table 7 presents ev-

[11] Sant'Anna (2018) show the importance of forest cover to the protection against extreme rainfall in urban environments.

idence of heterogenous effects on the extension of forest cover at the municipality level. Columns (1) and (2) display the effects of the interaction between drought and forest cover on lost area, whereas Columns (3) and (4) present the estimated coefficients for the value of agricultural output. We present results for the continuous mesure of drought - Rainfall deviation - and for the two dummies that represent moderate and extreme drought.

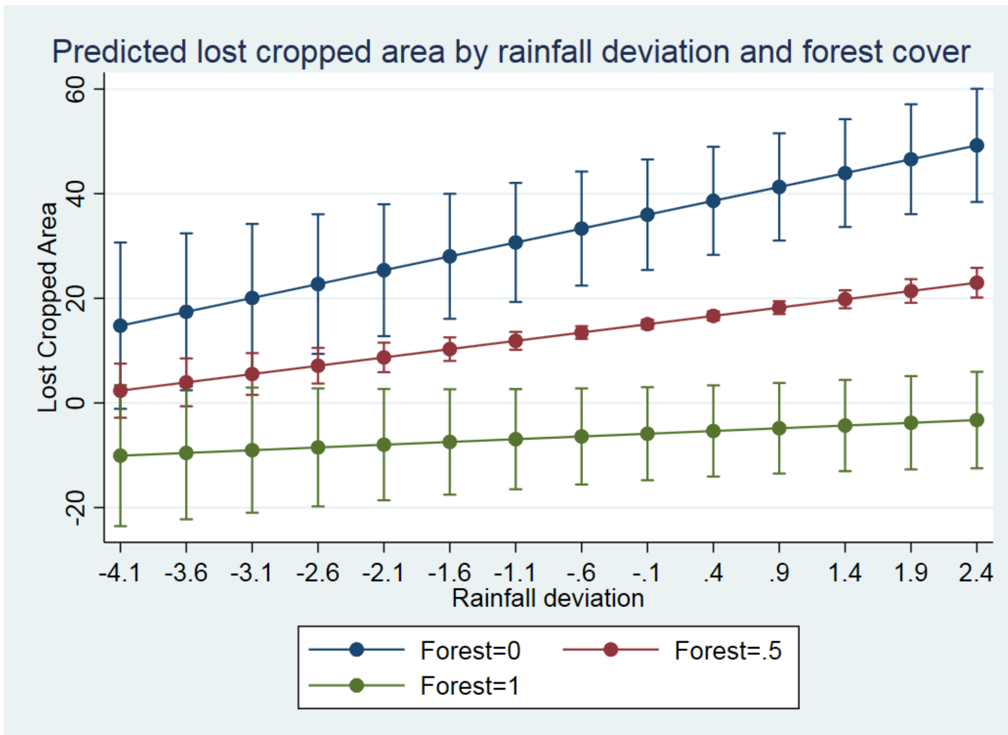
Table 7: Heterogeneity Effects - Forest Cover

VARIABLES	(1) Lost Area	(2) Lost Area	(3) Ln(Output)	(4) Ln(Output)
Rainfall deviation	5.303***		-0.161***	
	(1.227)		(0.051)	
% of Forest in Municipality Area	-42.294***	-39.115***	1.905***	2.004***
	(9.870)	(10.176)	(0.478)	(0.491)
Rainfall deviation x Forest Area	-4.257**		-0.003	
	(1.936)		(0.075)	
Dummy of Drought		6.780***		-0.110
		(1.679)		(0.087)
Drought x Forest Area		-6.318**		-0.164
		(2.688)		(0.139)
Dummy of Extreme Drought		12.000***		-0.469***
		(3.542)		(0.146)
Extreme Drought x Forest Area		-13.284**		0.380*
		(5.817)		(0.224)
Observations	15,128	15,128	15,143	15,143
R-squared	0.409	0.409	0.832	0.832
Municipality FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Cluster	Grid	Grid	Grid	Grid
Number of municipalities	1262	1262	1262	1262
Number of clusters	359	359	359	359

Note: Robust standard errors are clustered by grids. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Every specification has the expected results for the variables related to drought, with the expection of the dummy of moderate drought, on Column (4). More interesting, the presence of forest cover protects cropped areas from being lost and output losses. Therefore, forest cover has an effect of acting as a buffer of protection against losses when a drought shock strikes. A visual inspection of this result can be seen on Figure 3, which shows the margin plots of the interaction based on results from Column (1). It is clear from the Figure that the extension of forest cover provides an important protection against drought shocks, even for extreme drought (where rainfall deviation exceeds one, for instance).

Figure 3: Margin Plots of Column (1) of Table 7



Notes: The figure above depicts the predicted lost area based on the results of the interaction between rainfall deviation and forest cover.

5.4 Placebo and Robusteness tests

As argued before, given the structure of the data, there is spatial dependence in the variables that measure drought shocks. Therefore, it is necessary to adjust standard errors in order to overcome spatial correlation problems in the independent variable, as proposed by Conley (1999) and Hsiang (2010). Table 8 presents results comparable to results from Column (3), in Table 3, for lost area and from Column (1) - Table 4, for agricultural output. We work with different distance cutoffs, ranging from 50km to 200km. Columns (1)-(3) display results for lost area as dependent variable and Columns (4)-(6) present results for agriculture output.

As expected, the estimated coefficient is measured with increasing uncertainty as distance increases, however results remain robust to the increase of distance buffers, even for a distance as large as 200 km.[12] Thus, when we correct for spatial dependence using Conley procedures, results seem robust to spatial correlation problems.

Table 8: Effects of Drought Shocks - Conley Correction for Spatial Dependence

VARIABLES	(1) Lost Area Buffer 50km	(2) Lost Area Buffer 100km	(3) Lost Area Buffer 200km	(4) Ln(Output) Buffer 50km	(5) Ln(Output) Buffer 100km	(6) Ln(Output) Buffer 200km
Rainfall deviation	3.381***	3.381***	3.381***	-0.165***	-0.165***	-0.165***
	(0.621)	(0.882)	(1.134)	(0.024)	(0.034)	(0.045)
Observations	15,128	15,128	15,128	15,143	15,143	15,143
R-squared	0.007	0.007	0.007	0.009	0.009	0.009
Municipality FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Municipality Trend	N	N	N	N	N	N
Controls	Y	Y	Y	Y	Y	Y

Note: Standard errors are corrected for spatial dependence using Conley (1999), with distance cutoffs of 50, 100 and 200 kilometers. Column (1) Significance: *** p<0.01, ** p<0.05, * p<0.1.

An additional test to be performed relates to the timing of treatment. That is to say, one should expect to find a relationship between drought shocks and agricutltural outcomes only at the current year when treatment occurs. Therefore, on Table 9, we test whether rainfall deviation from previous and forward years affect our main dependent variables. This test works as a placebo where years other than the actual year of a drought should have no effect on lost area and on agricultural output.

Columns (1) to (3) present results regarding the impact on lost crop area. In Column (1), we test the effects of rainfall deviation in the previous year. Column (2) presents the results for forward year effects and Column (3) presents estimates considering previous, current and forward years. Every specification has municipality and year fixed effects, controls for temperature deviation and includes a municipality specific trend. Results are reassuring that our results are not driven by spurious correlation, since there is not any associated effect of previous and forward drought shocks on lost area.

Columns (4) to (6) reproduce the same structure of estimation using, instead, agricultural output as the dependent variable. As regards output, there is a positive association between previous drought shock and output, even when considering current effects (as in Column (6)). Forward effects are also slight positive in Column (5), but are not robust to the inclusion of previous and current drough shocks. However, one question remains: why

[12]A circle with a radius of 200 km has an area of 125,663 sq km, which is 13% of the Brazilian Semi-Arid total area.

should there be a positive effect on agricultural production one year after a drought shock? A possible explanation is given in the next subsection.

Table 9: Placebo test: effects of current, previous and forward years

VARIABLES	(1) Lost Crop Area	(2) Lost Crop Area	(3) Lost Crop Area	(4) Ln(Output)	(5) Ln(Output)	(6) Ln(Output)
Rainfall deviation$_{t-1}$	-0.696		-0.097	0.082***		0.036**
	(0.553)		(0.606)	(0.018)		(0.017)
Rainfall deviation$_{t}$			2.960***			-0.117***
			(0.679)			(0.028)
Rainfall deviation$_{t+1}$		-0.022	0.442		0.049*	0.034
		(0.775)	(0.764)		(0.029)	(0.031)
Observations	15,128	13,866	13,866	15,143	13,881	13,881
R-squared	0.513	0.537	0.539	0.878	0.886	0.887
Municipality FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Municipality Trend	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Cluster	Grid	Grid	Grid	Grid	Grid	Grid
Number of municipalities	1262	1262	1262	1262	1262	1262
Number of clusters	359	359	359	359	359	359

Note: Robust standard errors are clustered by grids. Significance: *** p<0.01, ** p<0.05, * p<0.1.

5.5 Deforestation as a response to drought

Table 9 shows a positive associaton between the deviation of precipitation in the previous year and current production, with no associaton with the current loss of area. A possible explanation relies on the fact that forest cover is a stock of biomass that can be converted into fertile soil, at least in the short term (Silva Neto et al., 2019), through slash and burn cultivation.[13] Therefore, inasmuch rural producers believe a drought shock in the previous year is random and there will be mean reversion to the historical average in the current year of cultivation, there is an incentive to clear land, in order to expand production. If this is so, we should expect a positive relationship between a drought shock in the previous year and deforestation in the current year.

Table 10 displays results for linear and non-linear effects of drought on the rate of forest loss. Column (1) displays a positive relationship between previous rainfall deviation and current deforestation. On Column (2), we provide the estimated coefficient for the current relationship, which is positive, albeit not statistically significative. When we consider an estimation with both current and previous drought shocks, as in Column (3), results are

[13] Most of the annual crops in Caatinga still use slash and burn system (Menezes et al., 2012). This is a historical process in Brazil, as described by Dean (1997).

robust only to previous rainfall deviation. From Columns (4)-(6), we reproduce the same exercise, using instead our meausures of moderate and extreme drought, in order to obtain estimates of a non-linear relationship. Indeed, results are more robust and stronger (3 times higher) for the dummy of extreme drought in the previous year. We conclude, thus, that extreme droughts are conducive to deforestation in the following year, as a way to recompose soil fertility in the short run.

Table 10: Effects of Drought Shocks on Deforestation

VARIABLES	(1) Forest Loss	(2) Forest Loss	(3) Forest Loss	(4) Forest Loss	(5) Forest Loss	(6) Forest Loss
Rainfall deviation$_{t-1}$	0.315*		0.319*			
	(0.179)		(0.183)			
Rainfall deviation$_t$		0.041	0.069			
		(0.242)	(0.243)			
Dummy of Drought$_{t-1}$				0.441		0.460*
				(0.271)		(0.277)
Dummy of Extreme Drought$_{t-1}$				1.480**		1.506***
				(0.595)		(0.581)
Dummy of Drought$_t$					0.103	0.190
					(0.442)	(0.435)
Dummy of Extreme Drought$_t$					0.012	0.183
					(0.612)	(0.604)
Observations	15,130	15,130	15,130	15,144	15,144	15,144
R-squared	0.572	0.572	0.572	0.527	0.526	0.527
Municipality FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Control	Y	Y	Y	Y	Y	Y
Cluster	Grid	Grid	Grid	Grid	Grid	Grid
Number of municipalities	1262	1262	1262	1262	1262	1262
Number of clusters	359	359	359	359	359	359
Mean of dependent variable	6.642	6.642	6.642	6.763	6.763	6.763

Note: Robust standard errors are clustered by grids. Significance: *** p<0.01, ** p<0.05, * p<0.1.

6 Conclusion

The Brazilian Semi-Arid is a region prone to suffer droughts. The low development of the region if compared to other parts of Brazil has always been associated to the climate conditions of the drylands. However, the frequent repetition of severe droughts led to extreme events, resulting in food insecurity, poverty and migration towards other parts of Brazil. But climatic conditions are not the only cause for the social vulnerability in the region: the concentration of economic and political power and the deficit of public policies maintains a vicious cycle of poverty and social vulnerability in the region.

As climate change is expected to increase the frequency and severity of droughts, we analyze the impacts of extreme drought shocks on agricultural outputs, namely lost area, value of agriculture output and yields in the region. Our results show that, even with adaptation, drought shocks have important impacts, substantially among crops used in family farming, with impacts on the living conditions of the poorest. We also assess heterogenous effects according to the provision of water supply and the maintenance of tree cover. These heterogeneous effects sign for the importance of sound public policies that provide an adequate stream of water and for the maintenance of forest cover, since it acts a buffer against drought shocks.

Finally, we also show that a common response among municipalities in the Semi-Arid is to expand the rate of deforestation in the following year after a drought shock. We interpret this result as an evidence that as rural producers believe a drought shock in the previous year will present mean reversion to the historical average in the current year of cultivation, there is an incentive to clear land, in order to expand production. This is so because trees represent a stock of biomass that can be converted in a fertile soil in the short term through slash and burn cultivation.

Overall, our results point to important effects of drought shocks in agricultural outputs. These effects are magnified when adequate infrastructure is lacking. Moreover, crops associated with family farming suffer significantly more, which we interpret as a sign that distributive effects are important as well. Therefore, despite climate change might increase the occurrence of severe droughts, our results show that there is much to be done in terms of public policies that can reduce the deleterious impacts of drought shocks.

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