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RESEARCH ARTICLE

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 long-run historical averages, on agricultural outcomes in a region that suffers recurrently from 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, as well as on crop yields. As we investigate distributional effects, our results show that crops related to familiar agriculture 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.

Keywords: agricultural output; Brazilian Semi-Arid; climate change; drought

JEL classification: Q54; Q56

1. Introduction

It is widely recognized that there is an anthropogenic contribution to the observed changes in climate. According to statements made in 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).

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As regards droughts, climate change is expected to alter their 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 on agricultural outcomes in the Brazilian Semi-Arid, the driest and poorest region in the country. We investigate how large deviations from historical averages in average rainfall 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 and correcting standard errors for spatial dependence (Conley, 1999), we use weather shocks – rainfall idiosyncratic shocks in our case – to 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.[1]

Our benchmark results show substantial effects of drought shocks on the loss of crop area and on the value of agricultural output. Considering non-linear effects, the results are more striking. We show that outcomes from crops related to familiar agriculture – beans and corn – are those that suffer from drought shocks, as highlighted by Cirino *et al.* (2015), since familiar farming suffers more from liquidity constraints to invest in adaptation than business agriculture.

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. We consider these to be the main contributions of this paper, since the extensive literature on drought shocks in the Brazilian Semi-Arid region has already detailed this phenomenon, but slight effort has been made to quantify the heterogeneous effects of drought shocks on the agricultural output in this region.

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 their population.[2] 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. On the other hand, Amare *et al.* (2018) assess the effects of negative rainfall shocks on agricultural productivity and its impact on household consumption. 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, which in our study is Brazil.[3]

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

[2] Burgess *et al.* (2017), for instance, assess the effects of high temperatures on mortality in rural India. According to the authors, potential mechanisms relate to lower productivity and wages in seasons with extreme hot days.

[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 per cent, with a significant variation.

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.

The paper is organized as follows. In section 2, we review and contextualize our object of study, highlighting the background of drought in the Brazilian Semi-Arid and reviewing the literature on climate shocks in this region. In section 3, we describe the database that we set up for this paper and in section 4, we explain the empirical strategy used. Section 5 presents the results found in this paper. Finally, section 6 briefly presents the main conclusions of this study.

2. Background

The Brazilian Institute of Geography and Statistics (IBGE) and the Northeast Development Superintendence 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 per cent (Medeiros *et al.*, 2012).[4] Therefore, the Brazilian Semi-Arid is the largest semi-arid territory in the world, as its area spans over 1 million km^2 and covers 1,262 municipalities, with a population around 25 million people.

Due to low soil fertility and water scarcity, the historical development of the region was not attached to plantations, as in the neighboring coastal zones of the Brazilian Northeast.[5] Therefore, cultivation in these interior lands was mainly carried out by subsistence farmers, with corn and beans being the most important crops since colonial times (De Castro, 1946; Prado, 2017).

This agricultural pattern remains similar in the present time: 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 low resilience to the increasingly frequent drought events, leading to high social vulnerability and major food and economic insecurity during these extreme events (de Alcântara Silva *et al.*, 2013; Travassos *et al.*, 2013; Costa, 2019).

Table 1 compares farming area, disaggregated in terms of family and business farming and specific crops, for the Semi-Arid region and the rest of the country. It is evident that family farming is far more important in the Semi-Arid region than in the rest of Brazil. As argued before, corn and beans still hold the lion's share of farming in those drylands: together, they account for 83 per cent of crop area in the Brazilian Semi-Arid, with the vast majority being from family farming (respectively, 83.6 and 88.5 per cent).

The historical vulnerability and poverty of the Semi-Arid population has captured the attention of policymakers since Brazilian independence. The perceptions and initiatives on how to proceed, however, vary widely, usually between two extremes (Campos, 2015). On the one hand, there are those who believe that adequate engineering civic works would be enough to solve the region's water scarcity problem. In this case, we can highlight the creation of the National Department of Works against Drought in 1909, aiming at the construction of cisterns, reservoirs and other hydrological infrastructure

[4]When evapotranspiration exceeds 60 per cent of precipitation every day of the year.
[5]For a history of sugarcane in the coastal zone of Pernambuco, see Rogers (2010).

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Table 1. Family and non-family crop patterns in Brazil

	Family farm Area (Ha)	Business farm Area (Ha)	Total farm Area (Ha)	Share of family Farm (%)	% of each crop in total
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	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	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.

and, more recently, the construction of the Transposition of São Francisco River Project, initiated in the mid-2000s.[6]

On the other hand, critics of this view argue that these infrastructure projects have high financial costs but little efficacy to solve the problems (Cirilo, 2008).[7] Thus, reflecting the opposite perception, the creation of the Superintendency for the Development of the Northeast in 1959 was originally intended to undertake the structural change in the region, with the support of many fiscal and credit incentives. Nevertheless, this approach has also failed due to 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 (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 Semi-Arid, still generates large losses in agricultural productivity (Cirino *et al.*, 2015). In turn, the extensive and unsustainable occupation of the Semi-Arid region is further compromising its lands,

[6]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.

[7]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.

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generating a phenomenon known as desertification, which decreases its humidity and soil productivity (Cirilo, 2008; Travassos *et al.*, 2013; Vieira *et al.*, 2015).

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 damages. 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. Hence, it is essential to understand which factors are capable of increasing resilience and guaranteeing food security for the Semi-Arid population in a context where climate change might bring increasing challenges to the region.

3. Data and descriptive analysis

3.1. Data

Our analysis relies on a balanced panel of yearly data at the municipality level on rainfall and agricultural outcomes from 2006 to 2017. The sample covers all 1,262 municipalities of the Brazilian Semi-Arid.

We use data agricultural output from the IBGE. We obtain data from the Brazilian Municipal Agricultural Survey (PAM). The variables used for the purpose of this study were: cultivated area and harvested area, in hectares; average productivity, in kilograms per hectare harvested; and value of agricultural production, in currency units (Brazilian Reais). All these variables are available at the municipal and year level, by crop. It is particularly interesting to observe the heterogeneity of results by crop type, since some 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 Semi-Arid.

We adopt a measure of lost area, which is measured as the difference between Ccultivated area and harvested area. According to the Food and Agriculture Organization of the United Nations (FAO) and PAM's own methodology, the difference between sown area and harvested area is related to no harvest due to damages and failures. Therefore, the difference between cultivated and harvested area is convenient for this study since, to evaluate drought-related losses, it is convenient to compare a counterfactual – cultivated area – in relation to an observed output – harvested area. Hence, we adopt the variable lost crop area, which is the percentage of area that was cultivated but not harvested from crop c in municipality i in year t. Moreover, we also evaluate the effects on the value of agricultural production and on specific crop yields.

In this paper, we want to evaluate the effects of drought on Brazilian Semi-Arid agriculture and test whether municipality-specific structures reflect heterogeneous drought resilience. Thus, we have collected different variables that can be divided into two groups: (i) climatic variables, which aim to identify drought events; and (ii) structural variables such as land use and water supply, which can capture heterogeneous effects on agriculture.

As regards drought events, we use the database *Terrestrial Air Temperature and Terrestrial Rainfall: 1990–2017 Monthly Grid Series, Version 5.01* (Matsuura and Willmott, 2018). This database presents monthly data of georeferenced rainfall and temperature – by 0.5×0.5 degree grids – between 1900 and 2017. In order to build a municipality by year dataset, we applied rainfall and temperature data from the closest pixel to each municipality's centroid. Then, we averaged monthly information into an annual basis (or quarterly basis, as we also want to inspect seasonal distinct effects).

After building the dataset, we calculated a continuous variable of annual rainfall deviation from the historical average for each municipality, in a way similar to Amare *et al.* (2018), according to the following equation:

$$\text{Rainfall deviation}_{it} = \frac{\text{mean}(\text{Rainfall}_{i1900-2017}) - \text{Rainfall}_{it}}{\text{sd}(\text{Rainfall}_{i1900-2017})},$$

where $\text{Rainfall : deviation}_{it}$ is the deviation of annual precipitation from the historical average for each municipality i in year t. Observations with positive Rainfall:deviation have less precipitation in year t than its mean precipitation from 1900 to 2017. We have calculated temperature deviations as well, in order to control for an important confounder for droughts.

One problem with using a continuous variable to identify an extreme event is that drought-related losses may not be linearly correlated with rainfall (for example, decreasing rainfall from 80 to 60 mm may not have the same effect as dropping from 50 to 30 mm, although the absolute variation is identical). Therefore, we also consider distinct alternative variables to assess drought shocks. Firstly, we build two dummy variables to identify drought events, according to the following principles:

$$\begin{cases} \text{if} : 0 < \text{Rainfall deviation}_{it} < 1, \text{then} : \text{Drought} = 1; \\ \text{if} : \text{Rainfall deviation}_{it} \geq 1, \text{then} : \text{Extreme Drought} = 1. \end{cases}$$

We also consider two additional sets of independent variables. We group rainfall bins according to different percentiles of the distribution. This allows us to assess non-linear effects in a more flexible manner. Finally, we split our measure of rainfall deviation into distinct quarters. By considering seasonal rainfall, we will be able to look at the most relevant measure of drought for distinct crop varieties.

In order to assess heterogeneous effects, we consider variables related to water supply and forest cover. The Brazilian Demographic Census, from 2010, provides the share of water supply in rural households by source. Therefore, we are able to calculate the share of rural households by municipality that have water supplied by: pipelines, groundwater (within and outside the household), rainfall and river. To deal with endogeneity concerns, we also calculate the share of each municipality area that is covered by water (either rivers or lakes), as of 2005, which is an alternative, arguably more exogenous measure of muncipality's dependence on rainfall as the main supply of water.

As we also study whether conserving native vegetation increases agricultural resilience to droughts, we set up an annual forest stock variable (as a percentage of total area occupied by municipality m) from the MapBiomas platform data which, through Google Earth Engine, assembles annual historical series of georeferenced land use data for the entire Brazilian territory (with 30×30 m precision).[8]

Finally, we utilize the ratio of tractors and rural employment by harvest area in 2006, the year of the Agricultural Census, as a way to control for the choice of inputs – capital and labor – that are relevant for agricultural production. As these variables are only available for this year, we will interact them with time fixed effects in order to control for the initial level of labor and capital while allowing for different paths among municipalities.

[8]We have selected the land use categories 1 to 9 to forest stock, according the Mapbiomas codes.

Table 2. Descriptive statistics

	Observations	Mean	SD	Min	Max
Panel variables					
Rainfall deviation	15,144	0.12	0.92	(3.44)	2.34
Dummy of extreme drought	15,144	0.16	0.36	–	1.00
Dummy of drought	15,144	0.45	0.50	–	1.00
Average monthly rainfall	15,144	64.26	24.99	11.05	229.83
Rainfall deviation Q1	15,144	0.28	0.72	(2.02)	2.23
Rainfall deviation Q2	15,144	0.01	1.08	(3.25)	2.38
Rainfall deviation Q3	15,144	0.15	0.84	(2.69)	3.29
Rainfall deviation previous Q4	13,882	0.09	1.00	(3.41)	2.66
Temperature deviation	15,144	1.03	1.12	(1.95)	4.94
Total lost area (%)	15,128	13.85	25.05	–	100.00
Lost area – beans (%)	14,773	16.21	30.30	–	100.00
Lost area – corn (%)	14,721	19.64	34.25	–	100.00
Ln (Output)	15,143	7.83	1.87	–	14.39
Ln (Yield) – beans	14,237	5.60	0.89	1.10	8.34
Ln (Yield) – corn	13,719	6.07	1.09	–	9.39
Native vegetation in municipality area (%)	15,144	0.54	0.25	0.01	0.99
Cross-section variables					
Pipeline water supply	1,262	0.32	0.24	–	0.98
Well water within property	1,262	0.14	0.14	–	0.72
Well water outside property	1,262	0.17	0.15	–	0.92
Water supplied by rain	1,262	0.21	0.22	–	0.95
Water supplied by river	1,262	0.13	0.14	–	0.92
Occupation/Harvest area	1,262	0.94	0.65	0.01	8.69
Tractors/Harvest area	1,262	0.01	0.01	–	0.18
Rainfall dependence (% of water area*100/total area)	1,262	0.80	2.01	–	30.54

Notes: Descriptive statistics computed at the municipality-by-year level for the entire period of analysis for which data are available. Cross-section variables are from the demographic census (those related to water supply, agricultural census (rural employment and tractors) and Mapbiomas (water potential). Variables are, respectively, evaluated at 2001, 2006 and 2005.

3.2. Descriptive statistics

Table 2 summarizes our main descriptive statistics. The variables in the top panel (panel variables) are at the municipality-by-year level, whereas the variables in the bottom panel (cross-section variables) are at the municipality level. These variables are used to assess heterogeneous effects and to control for the level of inputs utilized in agricultural production.

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We observe that yearly average lost area, as defined above, is 13.8 per cent in the Brazilian Semi-Arid municipalities. This is an extensive area and much higher than the rest of the country, which loses on average 1.2 per cent of planted area each year. The average lost area is high, but masks substantial variation among years. It ranges from a minimum of 5.0 per cent in 2011 to a maximum of 31.4 per cent in 2012. Another feature of the time series of lost area is that its size has significantly increased from 2012 on, as compared to previous years: from 2012 to 2017, the minimum achieved was 15.3 per cent, a much higher figure than the period 2006–2011, when the maximum was 9.0 per cent. As we analyze by crop type, average lost areas for beans and corn are respectively 16.2 and 19.6 per cent. Overall, the region has an important gap between sown and harvested areas, especially in crops related to family farming.

The occurrence of droughts is very prevalent in the Brazilian Semi-Arid and has been especially important in recent years. The average rainfall deviation is 0.12. In other words, from 2006 to 2017, rainfall deviation has been, on average, above the long-term mean by 0.12 standard deviation. Again, the main drought years are from 2012 to 2017. As we use our dummies of drought and extreme drought, we have 45 per cent of municipality-by-year observations with drought and 16 per cent of municipality-by-year observations under extreme drought. Finally, the mean monthly rainfall is 64.2 mm, which translates into 770 mm/year.

4. Empirical model

In this paper, we empirically estimate the effects of drought shocks and agricultural outcomes in the municipalities of the Brazilian Semi-Arid. We thus rely on a municipality-by-year panel and explore idiosyncratic variation in drought shocks across municipalities for causal identification.

As we estimate the effects on output value, as well as lost area and yields, we must consider that short-run weather effects – like the drought shocks we are evaluating – might have positive price effects due to a reduction in food supply, thus reducing the profit losses (Deschênes and Greenstone, 2007). We control for time fixed effects that might control for macroeconomic shocks across municipalities. However, our results for the output value might be underestimated as prices increase with quantity decreases.

Another possible source of concern is that farmers react to incoming information and adjust their input levels. Although we do not have information on yearly capital and labor, we add an interaction term of time fixed effects with capital and labor as of 2006, as defined in the previous section. Hence, our benchmark model to be estimated is:

$$Y_{it} = \beta_0 + \beta_1 \text{Drought Shock}_{it} + \gamma X_{it} + \alpha_t + \lambda_i + \alpha_t K_i' + \alpha_t L_i' + \varepsilon_{it},$$

where Y_{it} is a variable that measures agricultural loss. Throughout the paper, we 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 interactions of α_t with our measures of capital – K_i – and labor – L_i – represent a flexible way to deal with distinct paths of inputs by municipality, given their initial endowments. The model error term is ε_{it}.

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Our key identifying assumption relies on the hypothesis that drought shocks are uncorrelated with other determinants of agricultural production, conditional on municipality and year fixed-effects. That is to say, in order to recover a causal relationship between drought shocks and agricultural outcomes, we need to account for potential omitted variable bias that might arise from variables that vary over time and are correlated with drought and agricultural outcomes. As the region is inherently dry, it is plausible that individuals already adapt to local dryness. That is why we scale our main independent variable, rainfall deviation, by long-run standard deviation, which means that we are looking at intense variations in proportion to the municipalities' usual variation. Moreover, we include controls for time-varying factors that could affect agricultural outcomes as well, such as temperature deviations from historical averages. We also consider distinct trends of capital and labor use, given initial endowments as of 2006. Finally, as discussed before, the price effects can be especially important for the effects on output value. Hence, in alternative specifications, we also allow for municipality-specific time trends, which might help us in dealing with specific price trends by municipality. As it is not possible to control for all unobservable time-varying factors, we conduct some robustness checks and placebo tests as well.

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). It is then necessary to adjust standard errors in order to overcome spatial correlation problems in the independent variable, as proposed by Conley (1999) and Hsiang (2010). In order to account for this potential bias, we make use of two different strategies: (i) we apply 'Conley' spatial standard errors correction with a buffer of 200 km Conley (1999)[9] – all the main estimations use Conley correction; and (ii) with municipality time trends, we use robust standard errors clustered at the municipality level.

We also investigate how the effects can be heterogeneous conditional on the supply of water and on the amount of forest land. Thus, we also estimate the following equations:

$$Y_{it} = \beta_0 + \beta_1 \mathrm{DS}_{it} + \gamma X_{it} + \beta_2 \mathrm{DS}_{it} \mathrm{Water}'_i + \alpha_t + \lambda_i + \alpha_t K'_i + \alpha_t L'_i + \varepsilon_{it},$$

where DS_{it} is our measure of drought shock and *Water* is one of our measures of Water supply, as described in the previous section. A possible caveat with this estimation is that the kind of water supply and drought shocks might be correlated. In this case, our results should be interpreted with some cautioun, but it still allows us to have some confidence in the quality of how public policies are focused on municipalities with greater need.

Finally, we also estimate the following equation with heterogeneous effects by the share of native vegetation in the municipality area:

$$Y_{it} = \beta_0 + \beta_1 \mathrm{DS}_{it} + \gamma X_{it} + \beta_2 \mathrm{DS}_{it} \mathrm{NV}'_{ti} + \beta_3 \mathrm{NV}_{it} + \alpha_t + \lambda_i + \alpha_t K'_i + \alpha_t L'_i + \varepsilon_{it},$$

where NV_{it} refers to the share of native vegetation in the municipality's area. As native vegetation is important in the maintenance of the flow of water, it can be interpreted as

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

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an investment in adaptation (Ellison *et al*., 2012; Ilstedt *et al*., 2016). Hence, we expect municipalities with more native vegetation to suffer less from drought shocks.[10]

5. Results

In this section, we first report our main results on lost area and output value. We then explore effects by crop type, which represents a proxy for the difference for family and non-family farming. Finally, we explore heterogeneity by the supply of water, forest cover, and provide robustness checks and discussion.

5.1. Main results

This section presents the main results of the paper. To facilitate part of the discussion, figure 1 displays a binned scatterplot generated by regressing rainfall deviation and the total planted area lost in the left panel and output value (measure in *Ln*) in the right panel. Municipality fixed effects are also included. On the horizontal axis, the variable rainfall deviation measures how far away rainfall in a given year is from the long-term average, weighted by the inverse of the standard deviation in that same municipality, as defined in section 3.

A positive rainfall deviation implies that, in a given year, the long-term average rainfall is higher than rainfall in that year. Thus, it can be associated to a municipality-by-year drought shock. Negative values for rainfall deviation imply years with rainfall above the long-term average. Figure 1 shows that, on average, municipalities affected by higher rainfall deviation (more drought) have higher lost crop area. Furthermore, 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. In the right panel, we observe a negative relationship between output value and rainfall deviation. Hence, it seems that, after controlling for municipality fixed effects, there is a relation between drought shocks and negative agricultural outcomes that needs to be further investigated.

In table 3, we report our baseline results of the relationship between drought and agricultural output. Panels A and B report, respectively, the results for lost crop area and output value as dependent variables. In columns (1) and (4), we include only time and municipality fixed effects. We add production function controls in the second specification, columns (2) and (5). In the third specification – columns (3) and (6) – we add municipality-specific time trends, in order to account for specific unobserved factors varying in time. With the exception of this last specification, we correct for spatial dependence using Conley correction for standard errors. With municipality time trend, we cluster standard errors at the municipality level.[11]

In Panel A, in the first column, we find a positive effect of drought, as measured by rainfall deviation, on lost area. That is to say, when a municipality is hit by a drought of the magnitude of one standard deviation in relation to the long-term average, we observe a reduction of 3.38 p.p. in the harvested area as compared to sown area. This result is

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

[11]Online appendix table A1 displays the same estimations with standard errors clustered at the pixel level.

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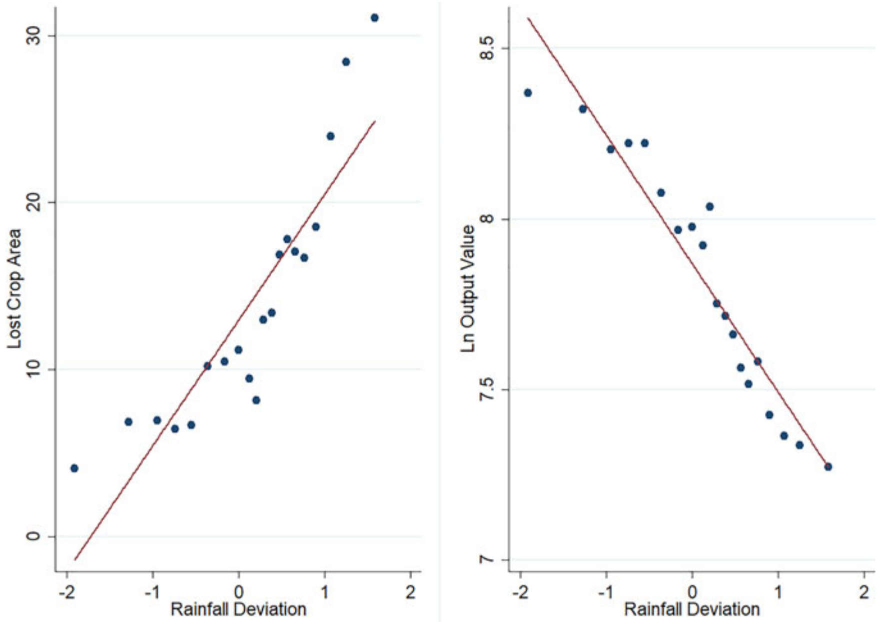

Figure 1. Scatter plot of residual rainfall deviation and lost crop area (left) and output value (right).

rather stable as we control for capital and labor as inputs (column (2)) and time trends specific to the municipality (column (3)).

As it appears from figure 1, it seems that there is a non-linear relationship as rainfall deviation achieves higher values. To test this hypothesis, columns (4)–(6) include dummy variables for years with high and extreme drought. We define the variable *Drought* as a dummy with value equal to 1 if *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. The inclusion of covariates follows the same pattern as columns (1)–(3).

The results from columns (4)–(6) are suggestive of a non-linear relationship, where extreme droughts appear to have an important effect on the loss of agricultural area. Compared to years without drought, a year with moderate drought has 3.75 p.p. more of lost area, according to the estimation from column (5), and years with extreme drought have 5.2 p.p. more lost area. In addition, the estimated coefficient for *Extreme drought* is 40 per cent larger than the estimated coefficient for *Drought*.

In Panel B, we evaluate the effects on agricultural output, which is what ultimately translates into farm income. The results estimated with rainfall deviation as the independent variable show a reduction between 15.6 and 17.4 per cent in the value of agricultural output. This sizable effect can be underestimated if prices react to the reduction in quantities produced, as discussed in the previous section. As we explore possible non-linear effects in agricultural output, our results show that moderate drought, using our definition, implies a loss of 16.3–20.4 per cent, according to the econometric specification. Extreme drought implies, as expected, higher losses, ranging from 24.7 to

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Table 3. Drought shocks effects on lost area and output value

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Dependent variable: Lost crop area						
Rainfall deviation	3.381*** (1.134)	3.342*** (1.119)	3.228*** (0.383)			
Dummy of drought				3.843*** (1.419)	3.755*** (1.396)	3.130*** (0.566)
Dummy of extreme drought				5.312** (2.417)	5.273** (2.385)	5.937*** (0.915)
Temperature deviation	−1.656** (0.671)	−1.654** (0.667)	−2.132*** (0.310)	−1.358** (0.646)	−1.369** (0.642)	−1.824*** (0.299)
Observations	15,128	15,128	15,128	15,128	15,128	15,128
Panel B. Dependent variable: Ln(output value)						
Rainfall deviation	−0.165*** (0.045)	−0.156*** (0.045)	−0.174*** (0.016)			
Dummy of drought				−0.204*** (0.056)	−0.191*** (0.055)	−0.162*** (0.024)
Dummy of extreme drought				−0.258*** (0.093)	−0.247*** (0.092)	−0.310*** (0.038)
Temperature deviation	−0.008 (0.025)	−0.005 (0.025)	0.024 (0.012)	−0.022 (0.024)	−0.018 (0.024)	0.007 (0.012)
Observations	15,143	15,143	15,143	15,143	15,143	15,143
Time and Municipality FE	Y	Y	Y	Y	Y	Y
Production function controls	N	Y	Y	N	Y	Y
Time trend	N	N	Y	N	N	Y
Conley standard error	Y	Y	N	Y	Y	N

Notes: Panels A and B report the results for lost crop area and output value as dependent variables. In columns (1) and (4), we include only time and municipality fixed effects. We add production function controls in the second specification, columns (2) and (5). In the third specification – columns (3) and (6), we add municipality-specific time trends. With the exception of this last specification, we correct for spatial dependence using Conley correction for standard errors. Significance: *** $p < 0.01$, ** $p < 0.05$.

31 per cent. That is to say, a municipality that suffers from extreme drought is expected to lose between one-quarter and one-third of the value of its agriculture output.

The results from table 3 imply remarkable losses. However, the effects of drought shocks might be very different depending on whether rainfall shortages are observed at the time of planting, when farmers can change their input mix to deal with drought, or whether rainfall shocks occur after the planting season. To test these possible distinct effects, we estimate with rainfall deviation measured quarterly. The planting season in the Brazilian Semi-Arid is mainly from October to December (the spring season in Brazil), especially for corn and beans, whereas harvest occurs mainly from April to June (but extends ultimately to July).[12]

[12]For the official agricultural calendar, see https://www.conab.gov.br/institucional/publicacoes/outras-publicacoes/item/7694-calendario-agricola-plantio-e-colheita.

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Table 4. Drought shocks effects on lost area and output value

	(1)	(2)	(3)	(4)
Panel A. Dependent variable: lost crop area				
Rainfall deviation previous Q4	−2.617*** (0.899)			
Rainfall deviation Q1		−0.938 (0.999)		
Rainfall deviation Q2			2.808*** (0.795)	
Rainfall deviation Q3				2.088** (0.994)
Observations	13,866	15,128	15,128	15,128
Panel B. Dependent. variable: Ln(output value)				
Rainfall deviation previous Q4	0.094*** (0.025)			
Rainfall deviation Q1		−0.081** (0.038)		
Rainfall deviation Q2			−0.110*** (0.030)	
Rainfall deviation Q3				−0.064* (0.037)
Observations	13,881	15,143	15,143	15,143
Time and Municipality FE	Y	Y	Y	Y
Production function and temperature controls	Y	Y	Y	Y
Conley standard error	Y	Y	Y	Y

Notes: Panels A and B report the results for lost crop area and output value as dependent variables. In every specification, we include time and municipality fixed effects, production function controls and temperature deviation as a covariate. We correct for spatial dependence using Conley correction for standard errors.
Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4 presents the results considering rainfall deviation from each quarter of the year. Column (1) presents estimates of the effects of rainfall deviation in the planting season, that is to say, the last quarter of the previous year. Column (2) presents the results for the first quarter of the current year. In column (3), our results relate to the effects of rainfall shocks in the harvesting season and column (4) presents the results for the third quarter of the current year.

Interestingly, our results suggest that when a rainfall shock strikes in the planting season, farmers can adapt in terms of their input choice, including land. Therefore, as one observes from column (1), rainfall deviation in the fourth quarter of the previous year – the planting season – is related to increases in output and no loss of planted area. On the other hand, when rainfall shocks happen in other quarters of the current year and especially in the harvesting season, the loss of sown area and agricultural output is more pronounced. Noack *et al.* (2019) find a negative impact of droughts during the planting season on crop income. These results, however, are not opposed to ours since the authors recognize that net crop income during that season is mainly affected by input expenditures. Hence, our results seem to go in line with those found by Noack *et al.* (2019) in a different context.

Table 5. Effects of drought shocks on different crops

	(1) Beans	(2) Corn	(3) Sugarcane	(4) Coffee
Panel A. Effects on lost crop area				
Rainfall deviation	5.050***	6.247***	−0.591	2.048
	(1.337)	(1.503)	(0.367)	(1.246)
Observations	14,773	14,721	6,402	2,328
Panel B. Effects on yield				
Rainfall deviation	−0.095**	−0.160***	−0.023	−0.074*
	(0.037)	(0.052)	(0.019)	(0.038)
Observations	14,237	13,719	6,391	2,309
Time and Municipality FE	Y	Y	Y	Y
Production function and	Y	Y	Y	Y
temperature controls				
Conley standard error	Y	Y	Y	Y

Notes: Panels A and B report the results for lost crop area and output value as dependent variables. In every specification, we include time and municipality fixed effects, production function controls and temperature deviation as a covariate. We correct for spatial dependence using Conley correction for standard errors.
Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results up to now imply a remarkable loss of agricultural outcomes when rainfall shocks are unanticipated by farmers and, for this very reason, cannot be adjusted by input changes. In this case, the distributive effects of rainfall shocks can be very important, since poorer farmers have less access to financial instruments and wealth to cope with the effects of drought shocks. Albeit we are not able, due to lack of available data, to assess this hypothesis directly, we move further to investigate the effects by different crops as a proxy for distributive effects.

5.2. Effects on different crops as a proxy for distributive effects

As previously discussed, the Brazilian Semi-Arid has an important share of familiar agriculture in the total share of agricultural activities. The main crops cultivated by families in the Semi-Arid are corn and beans, whereas business farms specialize 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 its potential distributional impact. Table 5 displays the effects, by crop, on lost area and productivity, as measured by the natural logarithm of each crop-specific yield. In Panel A, we present the effects on lost area, by crop. In 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 the historical average implies a loss of 5.0 per cent in cropped area with beans and 6.2 per cent in cropped area with corn. Columns (3) and (4) measure the effects on the loss of area on two crops associated moe with business farms – sugarcane and coffee. There is no sizable effect associated with rainfall deviation on lost area for those crops.

When one evaluates the effects on crop yields, the impact is more widespread. Results in Panel B show negative effects on yields for the four crops evaluated. However, the effects are again stronger, and more statistically significant, for beans and corns – which

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lose, respectively, 9.5 and 16 per cent of their yields – than for sugarcane and coffee.[13] Therefore, aside from important effects for the agricultural sector, drought shocks have negative distributive consequences as well.[14] Online appendix table A2 (online appendix) displays the estimates by quarterly rainfall deviation for bean and corn crops. Results are qualitatively similar to those presented in table 4, with major negative effects on agricultural outcomes coming from the harvesting season.

5.3. Heterogeneity

The results outlined so far highlight the need to understand how the characteristics of the municipalities might affect agricultural output. As previously discussed, drought shocks might have an impact on agricultural output heterogeneous to the level of investment in adaptation led by each municipality. Thus, in this section, we examine heterogeneity in the treatment effects since landholders and local governments can decide to invest in adaptation such as water availability and forest cover.[15]

Table 6 displays heterogeneous effects based on the provision of a fundamental public good: water. The table is divided into two panels. Panel A displays the effects on the loss of planted 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 provided by pipelines. In relation to lost area, the estimated coefficient of the interaction is negative, albeit not statistically robust. As regards the value of agricultural output, the coefficient of the interaction is positive and statistically significant. Taken together, it implies that the provision of a network of water supply has the effect of protecting producers from losing output, as well as sown area. Results from columns (2) and (3) provide a similar interpretation: having wells to collect groundwater – independently if being within property – also provides protection against drought shocks. From column (2), a back of the envelope calculation implies that for a drought with rainfall deviation equal to one standard deviation below the historical average and one-third of properties having wells within property, lost cropped area would be zero, instead of 5.4 per cent in the case where zero properties have wells.

Columns (4) and (5) display 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 loss of cropped area and output. In column (6), we use a somewhat more exogenous variable related to water supply: the share of the municipality area occupied by water (rivers, lakes, etc). Results are not significant either for lost area or for agricultural output. Online appendix table A3 displays the results with our measure of

[13]As noted by de Medeiros Silva *et al.* (2019), sugarcane is highly water dependent, as the majority of sugarcane crops occupy the coastal region instead the Semi-Arid region. In this sense, we can infer that sugarcane producers will only occupy the Semi-Arid if they are adapted to the adverse conditions in the region.

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

[15]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).

Table 6. Heterogeneity effects – water supply

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Effects on lost crop area						
Rainfall deviation	4.111*** (1.207)	5.368*** (1.205)	4.924*** (1.226)	2.581** (1.195)	0.366 (1.207)	3.243*** (1.121)
Rainfall deviation × pipeline water supply	−2.551 (1.692)					
Rainfall deviation × well water within property		−16.624*** (2.632)				
Rainfall deviation × well water outside property			−10.199*** (2.223)			
Rainfall deviation × water supply in river				6.974 (4.309)		
Rainfall deviation × water supplied by rain					10.731*** (2.272)	
Rainfall deviation × %water/municipality area						0.149 (0.126)
Observations	15,128	15,128	15,128	15,128	15,128	15,116
Panel B. Effects on Ln (output)						
Rainfall deviation	−0.233*** (0.047)	−0.222*** (0.049)	−0.231*** (0.050)	−0.110** (0.045)	0.002 (0.045)	−0.156*** (0.045)
Rainfall deviation × pipeline water supply	0.257*** (0.050)					
Rainfall deviation × well water within property		0.543*** (0.098)				
Rainfall deviation × well water outside property			0.487*** (0.093)			
Rainfall deviation × water supply in river				−0.415*** (0.098)		
Rainfall deviation × water supplied by rain					−0.570*** (0.079)	
Rainfall deviation × %water/municipality area						0.001 (0.005)
Observations	15,143	15,143	15,143	15,143	15,143	15,143
Time and municipality FE	Y	Y	Y	Y	Y	Y
Production function and temperature controls	Y	Y	Y	Y	Y	Y
Conley standard error	Y	Y	Y	Y	Y	Y

Notes: Panels A and B report the results for lost crop area and output value as dependent variables. In every specification, we include time and municipality fixed effects, production function controls and temperature deviation as a covariate. We correct for spatial dependence using Conley correction for standard errors.
Significance: *** $p < 0.01$, ** $p < 0.05$.

Table 7. Heterogeneity effects – forest cover

	(1) Lost crop area	(2) Lost crop area	(3) Ln output	(4) Ln output
Rainfall deviation	5.599*** (1.846)		−0.174*** (0.067)	
% of forest in municipality area	−43.304*** (11.728)	−39.742*** (11.944)	1.957*** (0.434)	2.021*** (0.433)
Rainfall deviation × forest area	−5.014* (2.771)		0.045 (0.082)	
Dummy of drought		7.069*** (2.113)		−0.126 (0.086)
Drought × forest area		−7.121** (3.452)		−0.103 (0.127)
Dummy of extreme drought		13.015** (5.670)		−0.524*** (0.184)
Extreme drought × forest area		−15.303* (8.910)		0.509** (0.247)
Observations	15,128	15,128	15,143	15,143
Time and municipality FE	Y	Y	Y	Y
Production function controls	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Conley standard error	Y	Y	Y	Y

Notes: In every specification, we include time and municipality fixed effects, production function controls and temperature deviation as a covariate. We correct for spatial dependence using Conley correction for standard errors.
Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

quarterly rainfall deviation at the harvesting season. The results are in line with those in table 6.

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). In this context, the maintenance of tree cover can be seen as an investment in adaptation; meanwhile it reduces the extension of land to be cropped – although it can increase income from forest extraction in drought events (Noack *et al.*, 2019). Thus, table 7 presents evidence of heterogeneous 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 measure of drought – rainfall deviation – as well as for the two dummies that represent moderate and extreme drought.

Every specification has the expected results for the variables related to drought, albeit the dummy of moderate drought, in column (4), is not robust. More interestingly, the presence of forest cover protects sown areas from being lost and from output losses, even without considering the interaction with our measures of drought. Finally, the interaction terms present, especially for the lost area as dependent variable, 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 in figure A2 (online appendix), which shows the margin plots of the interaction based on results from column (1). It is clear from the figure that the

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Table 8. Placebo test – effects of current, previous and forward years

	(1) Lost crop area	(2) Lost crop area	(3) Lost crop area	(4) Ln output	(5) Ln output	(6) Ln output
Rainfall deviation$_{t-1}$	0.073 (1.005)		1.181 (1.094)	0.052 (0.037)		−0.008 (0.039)
Rainfall deviation$_{t}$			5.025*** (1.176)			−0.195*** (0.046)
Rainfall deviation $_{t+1}$		0.943 (1.208)	1.278 (1.172)		0.003 (0.041)	−0.016 (0.040)
Observations	13,866	13,866	12,604	13,881	13,881	12,619
R^2	0.006	0.010	0.017	0.016	0.014	0.026
Time and municipality FE	Y	Y	Y	Y	Y	Y
Production function controls	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Conley standard error	Y	Y	Y	Y	Y	Y

Notes: In every specification, we include time and municipality fixed effects, production function controls and temperature deviation as a covariate. We correct for spatial dependence using Conley correction for standard errors.
Significance: *** $p < 0.01$.

extension of forest cover provides an important protection against drought shocks, even for extreme drought (where rainfall deviation exceeds one, for instance).

5.4. Robustness checks

In this subsection, we perform some additional robustness tests and provide a further discussion of our results. 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 agricultural outcomes only in the current year when treatment occurs. Therefore, in table 8, we test whether rainfall deviation from previous and forward years affects our main dependent variables. This test works as a placebo when years other than the year of a drought should have no effect on the loss of cropped 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 initial inputs interacted with time fixed effects. These tests provide reassurance that our results are not driven by spurious correlation, since there is no 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. Again, there is no associated effect of previous and forward drought shocks on agricultural output.

Finally, in table A4 in the online appendix, we test whether our results are robust to alternative specifications for drought shocks. In columns (1) and (3), we have a non-linear specification where we group rainfall into bins according to their percentile in the distribution of rainfall within each municipality. Results point to a significant non-linear relationship, where rainfall below percentile 5 is associated with losses of 14.3 per cent of the planted area and 59.9 per cent of agricultural output. In columns (2) and (4), we estimate a polynomial regression with rainfall and its square and cubic forms. The results also point to a non-linear relationship.

Overall, our results are in line with the literature on drought shocks and agricultural outcomes. Cirino *et al.* (2015) assess the impacts of El Niño in the Brazilian Semi-Arid. The authors find that bean and corn crops have, respectively, average losses of 48.6 and 53.8 per cent in a year when El Niño reaches the region. As regards sugarcane, there are no significant losses when this event occurs. Amare *et al.* (2018) finds that drought shocks – above the 0.5 threshold of rainfall standard deviation – in Nigeria cause a 39 per cent loss in agricultural productivity. The results are even more striking regarding corn yields: negative rainfall shocks reduce corn productivity by 59 per cent.

Many studies emphasize the importance of adapting to extreme events and climate change. For instance, Shahzad and Abdulai (2020) find, for Pakistan, that adapting agricultural practices reduces the impact of extreme climate events on agricultural production – causing less volatility in agricultural returns and decreasing the risk of production. The importance of access to water and irrigation to mitigate the effects of climate change is also highlighted by Seo (2011). Da Cunha *et al.* (2015) verify that irrigation as an adaptative strategy leads to increases in the value of agricultural property by decreasing the vulnerability of these establishments.

Finally, Noack *et al.* (2019) also investigate the effects of biodiversity as a buffer against drought shocks. The authors find similar results: drought shocks reduce crop income, but higher natural biodiversity can offset this negative effect. In addition, the mechanisms highlighted by Noack *et al.* (2019) – pollination, water retention and nutrient cycling – can be seen as environmental services, which are provided by native vegetation.

Hence, the results presented so far in this paper and the possible mechanisms that lead to adaptative strategies are confirmed by other studies in the same context, as well as in other contexts, which enhances confidence in the external validity of our results.

6. Final remarks

The Brazilian Semi-Arid is a region prone to droughts. The low development of the region as compared to other parts of Brazil has always been associated with the climate conditions of the drylands. The frequent repetition of severe droughts results in food insecurity, health impacts, poverty and migration towards other parts of Brazil. However, climatic conditions are not the only cause for the severity of social and natural disaster 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 severity of droughts, we analyze the impacts of extreme drought shocks on a diversity of agricultural outcomes in the region. Our results show that drought shocks have important impacts, substantially among crops used in familiar agriculture, with impacts on the living conditions of the poorest. We also assess heterogeneous effects according to the provision of water supply and the maintenance of tree cover. In this sense, we highlight the potential of these public goods to at least partially offset drought shocks in the Brazilian Semi-Arid.

Understanding that drought shocks are an important source of crop failure and agricultural losses and that this might lead to direct and indirect impacts on wellbeing, our results on mechanisms able to mitigate the effects of these shocks are an important

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subsidy for public policy. Therefore, this paper shows 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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