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Long-Term Effects of Drought on Local Labor Markets

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Abstract[1]

We examine the long-term impacts of drought on local labor markets in Brazil. Using rainfall data going back over a century, we build contemporaneous and historical drought indices for more than 3,000 local areas, and examine them in conjunction with five waves of population census data spanning 1970−2010. Results from a difference-in-differences design reveal that increased drought frequency in the previous decade reduces local value added, employment and wages in the agricultural sector; leads to job losses and pay cuts in the local manufacturing and services sectors; and induces out-migration, especially among younger cohorts, leading to relative population decline. These findings are in line with standard general-equilibrium theory featuring imperfect labor mobility across space.

JEL classification: J61; N96; O15; Q54; R11; R23.

Keywords: Local labor markets, migration, drought, climate change.

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1 Introduction

Increasing greenhouse gas emissions from human activities contribute to more volatile weather conditions, with several regions experiencing a higher frequency of extreme weather events such as droughts (IPCC, 2013). Standard models of spatial equilibrium suggest that workers and firms would optimally reallocate across sectors and locations in response to these shocks, mitigating their negative impacts. Empirical evidence on the nature and magnitude of these adjustments is necessary for designing effective policy responses to climate change. While a growing literature seeks to quantify the economic and social impacts of weather shocks, we still know relatively little about their long-term impacts on local labor markets.

In this paper, we address this issue by using a rich combination of rainfall and population census data for over 3,000 local areas in Brazil over the period 1970−2010. To guide our empirical analysis, we adopt the spatial general-equilibrium theory by Moretti (2011), featuring imperfect labor mobility and varying housing supply across locations. In the model, agricultural workers and firms optimally move across locations. However, labor mobility is imperfect because workers have idiosyncratic preferences for certain areas. A higher frequency of drought in the local agricultural economy reduces productivity, thereby lowering local wages and inducing some workers to migrate. While out-migration lowers the cost of housing in the affected areas, the purchasing power of the local wage rate falls nonetheless. And whereas labor mobility reduces real wages in the receiving areas, real labor income is not fully equalized across space because of imperfect mobility. The marginal worker that optimally chooses to remain in the drought-inflicted area has stronger preferences for that location than the corresponding marginal worker who preferred to stay in that location before the shock. Although labor is relatively cheaper in the affected area, it is also less productive. Therefore, real wage differentials persist across locations even in the presence of perfect producer mobility.

Besides direct negative impacts on the agricultural sector, such shocks may also affect other sectors of the local economy (Moretti, 2010). Inter-sectoral labor mobility within city boundaries leads to a general fall in the local wage rate. Together with the loss of agricultural jobs, this reduces the city budget constraint, depressing local demand for non-tradables. Fewer workers and lower earnings per worker lead to a fall in employment in sectors like retail, construction and legal services. While positive supply effects resulting from lower labor costs attenuate employment losses, they do not eliminate them. The implications of the shock for other tradable sectors like manufacturing are less clear-cut. On the one hand, the citywide reduction in wages makes these industries more competitive internationally, and hence more attractive for production location within the country. On the other hand, the shock may negatively affect manufacturing industries that are more sensitive to agglomeration economies.

We proceed to test those predictions using data in the Brazilian context. First, by using detailed rainfall data from 1901 to 2010, we construct contemporaneous and historical drought indices for minimum comparable areas, aimed at capturing yearly drought occurrences and quantifying the cumulative incidence of drought during the previous decade, respectively. We then link these measures to detailed information on local labor markets and economic activity from five recent population census waves. Using a difference-in-differences design−in a model that accounts for unobserved heterogeneity of local areas together with random trends at the local and regional levels−, we find that a higher frequency of drought during the previous decade reduces local value added, employment and adjusted wages (education-adjusted male earnings) in the agricultural sector. Also in line with the theory, out-migration rises, leading to relative population decline. Interestingly, migration flows in response to droughts are less prevalent among older cohorts and women, suggesting that these groups have stronger preferences for their original locations. As expected, employment and adjusted wages also fall in the services sector, since it predominantly comprises non-tradable activities. Adjusted wages in the manufacturing sector also fall. Perhaps more surprising is the fact that manufacturing employment also declines despite lower labor costs, pointing to the strong role of agglomeration economies.

This paper builds on and contributes to the growing body of literature seeking to quantify the economic and social impacts of weather shocks. Deschênes and Greenstone (2007) estimate the effect of year-to-year variation in temperature and precipitation on agricultural profits in US counties. Their preferred estimates indicate that climate change will increase annual agricultural profits by 4%. Burgess et al. (2011) examine the relationship between weather and death across Indian districts in the period 1957−2000, and find that hot days and deficient rainfall cause large and statistically significant increases in mortality within a year of such occurrences. They also show that hot and dry weather conditions in rural areas depress contemporaneous agricultural output and wages, and consequently raise agricultural prices.[2] A common approach in this strand of literature is to use short-run variations in temperature and rainfall to identify the economic and social impacts of changing climate conditions. We focus instead on the long-run effects of drought on local labor markets, including migration patterns and linkages between agriculture and other sectors of activ-

[2] Our paper is also broadly related to research that uses cross-national panel data to estimate the impact of changing weather conditions or natural disasters on aggregate GDP and exports, including the recent work by Jones and Olken (2010), Dell, Jones and Olken (2012) and Cavallo et al. (forthcoming). Additionally, at the country-product level, Bastos, Straume and Urrego (2013) examine whether and how governments around the world use trade policy strategically to mitigate the effects of rainfall shortages.

ity.[3,4] In doing so, our paper also relates to Michaels, Rauch and Redding (2012), who find that structural transformation that shifts jobs away from agriculture is an important driver of long-term patterns of urbanization, both in the United States and in Brazil. By showing that drought incidence has significant long-term effects on agricultural employment and migration flows from rural areas, our findings suggest that climate change may be an important factor underlying urbanization trends.

Our findings also relate to studies in the existing empirical literature that provide estimates on the impacts of climate shocks on a small subset of the labor market outcomes considered here, including local or regional wages (Jayachandran, 2006; Mueller and Osgood, 2009) and internal migration patterns (Hornbeck, 2012; Dinkelman, 2013). As discussed in more detail below, a key distinguishing feature of our paper is that it provides a comprehensive picture of how local labor markets respond to drought, and places the empirical analysis in the context of recent developments in spatial general-equilibrium theory.

Finally, this paper relates to the emerging theoretical and empirical literature examining long-run impacts of exogenous shocks or policy interventions on local labor markets, including Moretti (2010, 2011), Kline (2010), Autor, Dorn and Hanson (2013), Busso, Gregory and Kline (2013), Kline and Moretti (forthcoming,2013), and Cadena and Kovak (2013). Random weather fluctuations provide a useful source of variation for estimating the effect of exogenous productivity shocks in a given sector on local labor markets in the context of this framework. The quasi-experimental evidence we provide is in line with the spatial general-equilibrium theory by Moretti (2010, 2011), suggesting that this class of models offers a rich yet tractable framework for predicting how local labor markets around the world would adapt to climate change.

The remainder of the paper proceeds as follows. Section 2 outlines the theoretical framework for the empirical analysis. Section 3 describes data sources and provides descriptive statistics. Section 4 presents the empirical strategy. Section 5 reports and discusses our empirical results. Section 6 concludes.

[3] Our paper is also related to Maccini and Yang (2009) who focus on other long-term impacts of rainfall shortages by examining the implications of early-life rainfall for a range of adult outcomes observed later in life in Indonesia. They find that higher early-life rainfall leads to improved health, schooling, and socioeconomic status for women. By contrast, they do not find any relationship between early-life rainfall and adult outcomes among men.

[4] The use of explicit drought measures, as opposed to year-to-year variation in rainfall, is particularly interesting in the Brazilian context since droughts are the most prevalent form of extreme weather event experienced in the country. Between 2003 and 2008, around 300 municipalities per year issued emergency declarations due to drought, accounting for 70% of total emergency declarations associated with extreme weather events in this period.

2 A Model of Weather Shocks and Local Labor Markets

To guide our empirical analysis, we adopt the model of Moretti (2011), who extends the Rosen-Roback spatial general-equilibrium theory to allow for imperfect labor mobility and varying housing supply across locations. We use this framework to examine how local wages, employment, and demographic patterns might adjust when the local agricultural economy experiences a large and persistent rainfall shortage. We then provide an informal discussion on how the shock is likely to impact local economies with multiple (tradable and non-tradable) sectors of activity, building on Moretti (2010).[5]

2.1 Basic Setup

Consider a nation with two locations: city a and city b. Each city is a competitive economy that produces a single agricultural commodity. The commodity is freely traded internationally. Hence it has the same price in both cities−set equal to 1. Workers and firms move across cities to maximize utility and profits, respectively. However, labor mobility is imperfect, because workers have idiosyncratic preferences for location. Workers have homogeneous skills and each individual supplies one unit of labor. Thus, local labor supply is solely driven by the location decisions of workers. The indirect utility of individual i living in city $c \in \{a, b\}$ is

$$u_{ic} = w_c - r_c + A_c + \varepsilon_{ic} \tag{1}$$

where w_c is the nominal wage in city c; r_c is the cost of housing; and A_c is a measure of local amenities. The random term ε_{ic} represents worker heterogeneity in the valuation of city c. Examples of factors underlying such idiosyncratic preferences include family ties, the degree to which individuals are socially integrated in the local community, and cultural or ethnic identity.

Worker i's relative preference for city a over city b is:

$$\varepsilon_{ia} - \varepsilon_{ib} \sim U[-s, s] \tag{2}$$

where parameter s characterizes the importance of idiosyncratic preferences for location, and thereby the degree of labor mobility.

Local labor supply in city a is

$$w_a = w_b + (r_a - r_b) + (A_b - A_a) + s\frac{(N_a - N_b)}{N} \tag{3}$$

[5] The standard spatial general-equilibrium model was developed in the seminal contributions of Rosen (1979) and Roback (1982).

where N_c is the (endogenously determined) log of the number of workers in city c, while the total number of workers in the two cities $N = N_a + N_b$ is fixed by assumption. From (3), it is clear that worker preferences for location are a key driver of the elasticity of local labor supply: the larger is s, the less mobile are workers across cities, and thus the less elastic is local labor supply.

Agricultural production is represented by a Cobb-Douglas production function with constant returns to scale, such that:

$$\ln Y_c = X_c + hN_c + (1-h)K_c \tag{4}$$

where Y_c denotes agricultural output; X_c is a given productivity shifter specific to the city; and K_c is the log of capital. Firms move freely across locations to maximize profits. They are price takers and labor is paid its marginal product. The labor demand function in city c can therefore be written as:

$$w_c = X_c - (1-h)N_c + (1-h)K_c + \ln h \tag{5}$$

An international capital market provides an infinite supply of capital at a given price i. Each worker consumes one unit of housing, leading to an inverse demand function of the form:

$$r_a = (w_a - w_b) + r_b + (A_a - A_b) - s\frac{(N_b - N_{a)}}{N} \tag{6}$$

The model is closed by assuming that housing supply can be characterized as

$$r_c = z + k_c N_c \tag{7}$$

where the number of housing units in city c is equal to the number of workers there. The elasticity of housing supply, governed by the exogenous parameter k_c, reflects local geography and local land regulations. Equilibrium in the labor market is obtained by equating (3) and (5), while equilibrium in the housing market is given by equations (6) and (7).

2.2 Rainfall Shortage

To facilitate comparative statics, let us assume that cities a and b are perfectly identical in period 1. In period 2, a severe and unexpected rainfall shortage in city a causes drought, reducing the productivity of agricultural producers located there: $X_{a2} = X_{a1} - \Delta$, where $\Delta > 0$ gives the magnitude of the productivity shock. Local amenities remain unaffected and hence identical in the two cities.[6] The negative rainfall shock reduces the productivity of workers located in city a

[6] In reality, a severe rainfall shock may also negatively affect the quality of local amenities. The qualitative implications of the model would remain unchanged in that case.

compared with those in city b. The nominal wage in a falls by an amount equal to the productivity loss:

$$w_{a2} - w_{a1} = \triangle. \tag{8}$$

As a result, nominal wages in b become relatively higher, inducing some workers to move from a to b:

$$N_{a2} - N_{a1} = -\frac{N}{N(k_a + k_b) + 2s}\triangle \leq 0. \tag{9}$$

The number of migrants increases with the elasticity of labor supply (i.e., smaller s), and rises with the elasticity of housing supply in cities a and b (i.e., smaller k_a and k_b). Smaller s implies less importance accorded to idiosyncratic preferences for location, and therefore that labor is more mobile in response to real wage differentials. Smaller k_a and k_b indicate faster adjustment in housing supply to the change in demand for housing driven by migration. Out-migration causes the cost of housing in city a to fall, while the converse happens in city b. The magnitude of such drop is governed by the size of the shock ($\triangle$) and the relative elasticity of housing supply in a and b:

$$r_{a2} - r_{a1} = -\frac{k_a N}{N(k_a + k_b) + 2s}\triangle \leq 0 \tag{10}$$

The magnitude of the fall in housing costs is inversely related with the elasticity of housing supply in city a. Real wages in a decline nevertheless, since the fall in housing costs does not sufficiently compensate for the decline in nominal wages:

$$(w_{a2} - w_{a1}) - (r_{a2} - r_{a1}) = -\frac{k_b + 2s}{N(k_a + k_b) + 2s}\triangle \leq 0 \tag{11}$$

Although the rainfall shock occurs in city a, real wages in city b are also affected: in-migration increases demand for housing, pushing up property prices, thereby lowering the purchasing power of worker earnings.[7]

$$(w_{b2} - w_{b1}) - (r_{a2} - r_{a1}) = -\frac{k_a N}{N(k_a + k_b) + 2s}\Delta \leq 0 \tag{12}$$

Albeit labor mobility reduces real wages in city b, real labor income is not fully equalized across space since such mobility is imperfect. The marginal worker that remains in a now has stronger preferences for that location than the corresponding marginal worker before the shock. The difference in the relative preference for city a of the marginal worker is given by

[7] Migration from a to b might also be expected to affect nominal wages in both municipalities. However, the amount of capital employed by firms increases in a and declines in b, offsetting the changes in labor supply.

$$(\varepsilon_{a2} - \varepsilon_{b2}) - (\varepsilon_{a1} - \varepsilon_{b1}) = \frac{2s\Delta}{N(k_a + k_b) + 2s} \geq 0 \tag{13}$$

While labor is relatively cheaper in a, it is less productive. Therefore, real wage differentials persist across locations even in the presence of perfect firm mobility.

2.3 *Multiplier Effects in a Multi-sector Local Economy*

Assume now, as in Moretti (2010), that each city produces a vector of internationally traded goods whose price is given (including the agricultural product examined above) and a vector of non-traded goods whose price is determined locally. Workers move freely across sectors within city boundaries. Hence there is no heterogeneity in the marginal product of labor or wages within cities. As before, local labor supply is upward sloping, with an elasticity that increases by the degree of labor mobility across cities.

A rainfall shortage naturally decreases output and employment in the agricultural sector. However, in a multi-sectoral local economy, this shock may also affect employment in the rest of the local economy (other tradable sectors and the non-tradable sector). In general equilibrium, the shock has implications for local prices: free inter-sectoral labor mobility within the city implies that wages of all local workers fall, provided labor supply is not infinitely elastic; the cost of housing also falls, unless housing supply is infinitely elastic.

First, consider the likely impacts of the shock on the non-tradable sector. The decline in agricultural wages and jobs implies that the city budget constraint has declined, lowering local demand for non-tradable goods. Employment in the service sector (e.g. retail and construction) falls because the city now has fewer workers and each worker has lower earnings (implying that the overall demand for these services is lower). The magnitude of these negative impacts will be larger in the presence of stronger consumer preferences for non-tradable goods and higher labor utilization in the non-tradable sector (due to a larger multiplier effect). Offsetting general equilibrium effects on wages and prices also come into play: all else equal, lower labor costs contribute to a rise in the supply of local services, mitigating (but not eliminating) the negative effect resulting from reduced demand.

The impact of rainfall shortages on employment in other tradable sectors like manufacturing is less clear-cut. Two forces are at work in this case, affecting manufacturing employment in opposite ways. On the one hand, the city-wide reduction in wages makes these local industries more competitive. Since the price of this good is set internationally, in the long-term the city is likely to attract more producers from other parts of the country. On the other hand, if agglomeration economies are important, the fall in local output in the agriculture and services sectors may lead to a loss of manufacturing activity.

3 Background and Data

Brazil has a population of about 192 million spread over 3.2 million square miles. The country is divided into 26 federal states and one federal district. Federal states are divided into over 5,500 municipalities. Although municipal boundaries do not cross state lines, they have changed over time. For this reason, we will focus on Minimum Comparable Areas (MCAs) as our unit of analysis. MCAs are clusters of contiguous municipalities that are stable over time.[8] For simplicity, we will refer to MCAs as cities. There were 3,659 cities during the period 1970–2010, each with an average area of about 900 square miles. This is approximately equal to the 35^{th} percentile area of metropolitan areas in the United States (and about one-fifth the size of the Washington DC-VA-MD metropolitan area).

3.1 Data Sources

We combine information from several sources to build a panel data set of cities spanning four decades. Population and migration data have been obtained from the Brazilian Population Census of 1970, 1980, 1991, 2000, and 2010. The micro data are produced and published by the Brazilian Institute of Geography and Statistics (IBGE) and consist of a 20% stratified random sample of the total population. The sampling scheme adopted results in an overrepresentation of the smaller cities. We use information on population, employment, sectoral employment, wages, education level, age, gender, race, and marital status for our analysis. We also use population census information regarding the location of households five years before the census was administered to determine migration inflows and outflows of each city.

Annual data on municipal agricultural value added have been obtained from the Institute for Applied Economic Research (IPEA), though the primary source for this is also the IBGE.[9] Additionally, we draw from IPEA the income component index of human development indicators, available for the 1970–2000 period.[10]

[8] The Minimum Comparable Areas (Areas Minimas Comparaveis) were created by the Instituto de Pesquisa Economica Aplicada (IPEA).

[9] These data are fully integrated with the series of standard National Accounts of Brazil.

[10] Municipality-level data at 10-year intervals are usually available for the period before 1991. To link these data with population census data obtained from IBGE, these outcomes are combined at the MCA level using IPEA's own municipality to MCA correspondences. MCA level data were available from 1991 to 2000 therefore linking them with the 1970-1991 data was straightforward. We include the series harmonization that took place due to the 1991 break. Data on this indicator are not yet available for 2010.

Rainfall data for the period 1901–2010 come from the Climate Research Unit (CRU) at the University of East Anglia.[11] The data provide a comprehensive global geo-referenced grid with $0.5° \times 0.5°$ resolution of monthly weather indicators. We follow a three-step procedure to compute city-level rainfall data. First, we determine the coordinates of the center of each cell in the grid. Second, using the center of the city as our target, we interpolate the data using a geo-spatial (kriging) procedure in each monthly cross-section to estimate city-level precipitation. Third, in the few cases where interpolation yields negative rainfall values, we replace them with zeros. In a recent paper, Auffhammer et al. (2013) argue that global climate data sets, especially those that measure precipitation, could significantly vary from one to another. For robustness, we also compute drought measures using the Matsuura and Willmott (2012) data set, which has the same resolution and time coverage as the CRU data set, but uses a somewhat different interpolation method.[12]

To further validate our weather-based drought measures, discussed in more detail below, we use administrative data on emergency declarations from the National Secretariat of Civil Defense (NSCD), which is available only for a short time span (2003–2008). This data set contains information by city on the types of extreme events (flood, drought, storms, etc.), types of emergency declared (state of emergency or state of public calamity), and starting date and duration of the declaration. Using these data, we construct a measure of the number of droughts declared each year in each city.

3.2 Constructing Drought Indices

In line with Palmer's (1965) seminal work and much of the subsequent literature, we define droughts as instances of prolonged and abnormal moisture deficiency. To identify such instances in the data, we rely on measures of deviations of local rainfall from the corresponding regional distribution recorded in previous decades.[13] We use data on the average precipitations during the rainy season in the climatological region where each city is located as a benchmark to capture demand for soil moisture. Agricultural activity is planned on the basis of regional weather patterns. Sowing and harvesting, for instance, take place in pre-defined seasons. A rainfall shortage is not

[11] The data can be found at http://www.cru.uea.ac.uk/cru/data/hrg/ (we used the CRU TS 3.2 dataset).

[12] We do not use the NCEP/NCAR data set analyzed by Auffhammer et al (2013) since its resolution is significantly different. As Auffhammer et al (2013) point out, while CRU and UDEL have a resolution of $0.5° \times 0.5°$, the NCAR/NCEP has a resolution of $1.875° \times 1.9°$, which would yield only 1/3 of the observations of the CRU or Matsuura and Willmott (2012) data sets.

[13] Ideally, we would have liked to use the Palmer Drought Severity Index which captures the soil moisture deficiency in each municipality-year (Palmer, 1965). However, doing so would require estimating supply and demand of soil moisture using data on precipitation, temperature and a set of calibrated municipality-specific coefficients that determine the demand in each region based on evapotranspiration, recharge, loss and runoff rates. Unfortunately, the information required to compute such coefficients is not available causing most studies in the literature to rely on precipitation-based measures (Gibbs and Maher, 1967).

likely to result in sizable output losses if it occurs in a season that is expected to be dry. On the other hand, abnormally low rainfall in a rainy season is very likely to have pervasive effects.

We consider that city c suffered a drought in year t if the average precipitation in the rainy season was below the $20th$ percentile of historical precipitation in the climatological region s. Specifically, for each city c located in climatological region s we define a dichotomous variable $D_{sct} = 1\left(p_{sct} < P^{20}_{st} \middle| \; c \in s\right),$ where p_{sct} is the average precipitation during the rainy season and P^{20}_{st} is the $20th$ percentile of the distribution of precipitation in climatological region s over the period $\{1900, ..., t-1\}$.[14]

The rainy season for each city was determined based on its climatic region s, and by averaging rainfall by season. We first classify cities based on the Köppen-Geiger climate classification index which divides Brazil into nine regions.[15] Seasons are then defined as follows: spring from October to December, summer from January to March, fall from April to June, and winter from July to September. We compute average precipitation from 1901 to 1970 for each climatic region and season. For each climatic region, rainy seasons are defined as the season with the highest average precipitation.

Since our outcome data is measured by decade, we capture the history of droughts H_{sct} taking into account contemporaneity and total duration of annual droughts D_{sct} up to year $t-1$. We define the historic drought index as

$$H_{sct} = \frac{1}{9}\sum_{\tau=1}^{9} \frac{d_{sc,t-\tau}}{(1+\rho)^{\tau-1}} \tag{14}$$

where ρ is the rate at which droughts in previous years are (geometrically) discounted and d_{sct} is the number of continuous droughts in the years immediately before year t. This is expressed as follows,

$$d_{sct} = \sum_{J=0}^{9} 1\left[(D_{sc,t+1} = 0) \text{ and } (D_{sc,t-j} = 1 \,\forall\, j \in \{0, 1..., J\})\right] \tag{15}$$

where $1[\cdot]$ is an indicator function that equals 1 if the argument is true and 0 otherwise. Thus, if there is a drought in year t and no drought in years $t-1$ or $t+1$, then $d_{sct} = 1$. If there is a drought in years t and $t-1$, but no drought in $t-2$, then $d_{sct} = 2$. If there is a drought in $t,\ t-1$, and $t-2$ then $d_{sct} = 3$, and so on. Note, though, that in order to avoid double counting, in the previous two examples the formula would still yield $d_{c,t-1}$ and $d_{c,t-2}$ equal to zero. The

[14] Alternatively, we could have used the standardized precipitation index (SPI) by McKee, Doesken and Kleist (1993). We find that the SPI is highly correlated with our drought measure.

[15] These are the nine climate classifications: (1) Tropical – Rainforest; (2) Tropical – Monsoon; (3) Tropical wet and dry climate – dry season; (4) Tropical wet and dry climate; (5) Arid – Steppe – Hot; (6) Temperate – without dry season – hot summer; (7) Temperate – without dry season – warm summer; (8) Temperate – dry winter – hot summer; and (9) Temperate – dry winter – warm summer.

index H_{sct} is bounded by 0 and 1. It will equal 0 if no droughts were observed in the previous nine years. It will take the value 1 if there was a drought in every single year, in which case $d_{sct-1} = 9$, $d_{sct-2} = \cdots = d_{sct-9} = 0$.

Drought impacts depend on its timing, duration, and severity. The historical drought index presented here is constructed to capture: (i) the timing of the drought by discounting older events relative to newer ones and (ii) the duration of the drought by "not discounting" consecutive droughts and considering them as one event.[16] We choose $\rho = 0.15$, which is consistent with the private discount rate used in developing countries. However, our results are quite robust to choices of any $\rho \in [0.05, 0.35]$.

3.3 Descriptive Statistics

Figure 1 depicts the spatial distribution of drought frequency (D_{sct}) in Brazil during the period 1970–2010. Droughts have been more frequent in the eastern part of the country, especially in the northeast. These areas account for about 24% of national GDP and 27% of the total population. Figure 2 uses the NSCD data set to plot the number of emergency declarations caused by droughts over the period 2003–2008. We observe that the spatial distribution of emergency declarations due to drought in this period is fairly similar to that of our weather-based measures. This supports the validity of our key independent variable. For further robustness, we compute D_{sct} using the Matsuura and Willmott (2012) data set. We find that these measures coincide 94 percent of the time with those based on the CRU data set. Figure 3 plots the historical index for each decade from 1970 to 2010. We observe a similarity in the distributions of these indices over time, with a high frequency of observations at zero and a quasi-exponential distribution for positive values.

In Table 1, we report basic descriptive statistics for two different samples of the data for 1970 (the first year of our data set) and for the period 1960–1970. Column (1) presents the means of all characteristics for all cities, while column (2) restricts the analysis to rural areas, defined as cities where the share of agricultural value added is higher than 50% in 1970. We see that rural areas tend to have less population and lower relative endowments of skilled labor. The age distribution of the population and the degree of drought incidence are fairly similar across sub-samples. Finally, we observe that agricultural value added and population grew more slowly in rural areas during the 1960s. Our econometric model will feature city fixed-effects, random city trends, and region-year effects to account for this heterogeneity.

[16] The use of dummy variables to measure droughts does not allow us to differentiate individual droughts with regard to the magnitude of the deviation of rainfall from the normal level. This is nevertheless in line with much of the previous literature, where the duration of drought has been deemed to be much more important than the magnitude of the rainfall shortage at any given time.

4 Empirical Strategy

While the model in Section 2 emphasizes the long-term and general-equilibrium effects of drought, empirically it is useful to distinguish between short- and long-term effects. Droughts can have obvious contemporaneous negative impacts on agricultural output. Perhaps more interestingly, the repeated occurrence of droughts is likely to have long-term consequences on local labor markets by affecting soil quality and location decisions of workers and firms. We estimate both the contemporaneous (D_{sct}) and historical (inter-censal) cumulative (H_{sct}) effects of droughts on a set of outcomes Y_{sct} in city c in (climatic) region s at time/decade t. The set of outcomes we consider include the logs of value added, wages, employment, population, as well as the out-migration and in-migration rates.

We start by assuming that outcomes follow a data generating process of the form:

$$Y_{sct} = \theta W_{sct} + g_{sc} + b_{sc}\, t + r_{st} + u_{sct}\ , \tag{16}$$

where W_{sct} is a variable that measures the volume of rainfall and parameter θ denotes its effect on the outcome of interest.

This model includes city fixed-effects, g_{sc}, that capture all time-invariant unobservable differences between cities that might affect income, labor market outcomes, or population. For instance, some cities might be more prone to experiencing a drought, may have a different economic structure, infrastructure, or migration network that influence the way in which droughts impact the outcomes of interest. The model also includes a random (linear) time trend, b_{sc} that accounts for the fact that some cities are growing, gaining population, or becoming more productive over the 40-year period under analysis. Finally, we also include region-year fixed-effects, r_{st}, which control for shocks that are common to all cities within the same climatic region. These shocks include national and regional droughts, region-wide differential trends in economic activity, migration, demographics, aggregate economic policies, and other factors that affect the outcomes of interest.

We estimate the (reduced-form) effect of droughts on local labor market outcomes using a difference-in-differences design. Taking the first difference of (16) we can eliminate the city fixed effect g_c. In particular

$$\Delta Y_{sct} = \theta \Delta W_{sct} + b_{sc} + \eta^*_{st} + u^*_{sct}. \tag{17}$$

where $\eta^*_{st} = \eta_{st} - \eta_{st-1}$ is a region-specific trend in the growth rate of the outcome of interest and $u^*_{sct} = u_{sct} - u_{sct-1}$. The variable ΔW_{sct} denotes the occurrence of a drought either in year t or in the previous nine years. We parameterize $\theta \Delta W_{sct} = \theta_1 D_{sct} + \theta_2 H_{sct}$ and interpret θ_1 as the short-term or contemporaneous impact of a drought on the dependent variable and θ_2 as the medium/long-run impact.

The validity of the causal estimate of droughts (θ_1, θ_2) depends on the assumption that $E\left[(D_{sct}, H_{sct})\, u^*_{sct} \middle|\, b_{sc}, \eta^*_{st}\right] = 0$. By conditioning on city and region-year fixed effects, coefficients are identified from city-specific deviations in drought incidence after accounting for shocks common to all cities in each region. Since drought incidence at this small geographical level is basically unforecastable and random, we assume it is orthogonal to the error term u^*_{sct}. In other words, the key identification assumption is that no shocks to population, economic activity, or local development are systematically related to city-specific droughts.

By assuming that workers have homogeneous skills, the model in Section 2 emphasizes average impacts on local wages. In reality, however, workers have different levels of human capital that are likely to translate into different marginal productivities, and therefore wages. To account for this heterogeneity, we compute education-adjusted local wages. For each period $t \in T = \{1970, 1980, 1991, 2000, 2010\}$ we estimate the following equation

$$\log(wage)_{ict} = \beta_0 + \beta_1 Edu^1_{ict} + \beta_2 Edu^2_{ict} + ... + \beta_6 Edu^6_{ict} + \varphi_{ct} + e_{ict}$$

where $\log(wage)_{ict}$ is the logarithm of wages of 15-59 year old males for city c and $\left\{Edu^j_{ict}\right\}_{j \in J}$ is a collection of exhaustive and mutually exclusive educational dummies which cover the entire range of educational categories J ranging from incomplete primary level of education to education beyond university-level. The estimated $\widehat{\varphi}_{ct}$ is the average residual wage of the city c after accounting for the education level of the city population. The change in residual wages can then be computed as $\widehat{\varphi}_{ct} - \widehat{\varphi}_{ct-1}$.

In all our specifications we correct our standard errors to allow for arbitrary forms of heteroskedasticity, arbitrary forms of serial correlation and (a certain type of) spatial correlation of the error term u^*_{sct} by using a two-way clustering on the latitude and longitude of the city (Cameron, Gelbach and Miller 2011).[17]

5 Results

5.1 Main Results

Table 2 reports our estimates of the effects of drought on the main economic outcomes considered. Results for each outcome are presented in a different row. While our main focus is on the long-term impacts of droughts –captured by the coefficient associated with the historical drought index (H_{sct})–, we also examine the point estimates associated with the contemporaneous drought

[17] We divide the country into a grid of 100 latitude bands and 100 longitude bands and we cluster on both grids.

indicator, D_{sct}. Since rural communities are more exposed to the potential adverse effects of severe rainfall shortages, we are mainly interested in the estimates for the sub-sample of cities that are predominantly rural –shown in columns (1) and (2). Cities are classified as rural if the share of agricultural value added in local income exceeded 50% in 1970. For comparison, in columns (3) and (4), we also examine the full sample of cities where we expect to find weaker impacts on the outcomes of interest.

The estimates in columns (1) and (2) provide evidence of negative short- and long-term effects of drought on agricultural output. The negative contemporaneous effect is in line with the assumption that rainfall shortages reduce labor productivity in the agricultural sector. The negative long-term effect is consistent with the hypothesis that the repeated occurrence of drought is likely to have long-term consequences for local labor markets, by affecting soil quality and location decisions of workers and firms. Although our data do not allow us to directly estimate impacts on soil quality, they make it possible to investigate further supporting evidence about impacts on wages, migration patterns and employment.

The estimates reported in Table 2 point to negative short- and long-term effects of drought on local adjusted wages (that is, labor compensation adjusted for the education level of the local population). This finding supports the theoretical prediction that local wages adjust downwards in response to a fall in the marginal product of labor caused by a drought. In the face of lower pay for a given level of education, some workers may optimally decide to move away from the drought-inflicted areas, leading to a relative decline in local employment, population and income. The results reported in the remainder of Table 2 support these theoretical predictions. A higher frequency of drought leads to higher rates of out-migration, both in the short and long term. Furthermore, we observe negative impacts on local population, employment and income. The estimates on the impacts of drought on in-migration are negative, but statistically insignificant, suggesting that population adjustments following higher drought incidence mainly comprise labor movements away from drought-inflicted areas. As expected, a comparison between columns (1)-(2) and columns (3)-(4) reveals that these effects tend to be considerably larger in rural areas than in the full sample. We further notice that while contemporaneous impacts are generally less precisely estimated they tend to go in the same direction as long-term impacts.

As discussed in Section 2, besides its direct negative impacts on the agricultural sector, a greater drought occurrence may also affect other sectors of the local economy. In the long-term, inter-sectoral labor mobility within the city would be expected to lead to a generalized decline of the local wage rate. The results reported in Table 3 support this prediction. The coefficient of the historical drought index is negative and statistically significant in all the three broad sectors considered: agriculture, manufacturing and services. Furthermore, the magnitude of this negative effect is fairly similar across these sectors, as would be expected in the presence of inter-sectoral labor mobility. Along with the loss of agricultural jobs (as agricultural workers move elsewhere), this fall in the city-wide wage rate would be expected to depress local demand for non-tradables, leading to job losses in services. The results in column (2) indicate a negative (long-term) multiplier effect on that sector. The implications of the shock for other tradable sectors like manufacturing are ex-ante more ambiguous. On the one hand, the city-wide reduction in wages makes these industries more competitive internationally, and thus more attractive for production location. On the other hand, the shock may have negative implications for manufacturing industries that are more sensitive to agglomeration economies. Interestingly, the results in column (2) reveal that local manufacturing employment also declines despite lower labor costs, indicating strong agglomeration economies.

The results presented so far strongly suggest that migrating away from drought-inflicted areas is a strong adaptation mechanism to this extreme weather event. Based on the theoretical model presented in Section 2, there are reasons to expect some degree of heterogeneity in the intensity of such migration movements across groups of the local population. In the model, labor mobility is assumed to be imperfect because workers have idiosyncratic preferences for certain locations. In the face of a large and persistent rainfall shortage, workers with weaker preferences for the drought-inflicted areas optimally decide to migrate, as the utility gain associated with a higher wage elsewhere more than compensates for the loss in utility involved in relocating. The results in Table 4 reveal that a stronger incidence of drought over the previous decade induces out-migration across all population groups considered (column (2)). Interestingly, these estimates also suggest that out-migration is relatively less prevalent among older cohorts, females and married citizens, suggesting that these groups exhibit stronger preferences for the drought-inflicted areas. The results in this table further confirm the earlier finding that virtually all adjustments in the local population following droughts are due to stronger out-migration and not lower in-migration.

5.2 Robustness

To assess the robustness of our findings, in Table 5 we estimate alternative specifications of equation (17) for the main outcomes of interest, focusing solely on the sub-sample of rural areas. Column (1) presents the baseline results reported in the first two columns of Table 2. Columns (2) and (3) report results from analogous regressions, but using alternative discount rates in the construction of historical drought indices: $\rho = 0.05$ and $\rho = 0.25$, respectively. We observe that our main results are not sensitive to the use of alternative discount rates: the magnitude and statistical significance of the coefficients of interest remain very similar to the baseline estimates.

We proceed by verifying the extent to which our results might be driven by a small subset of local areas. To this end, in Column (4) we restrict the sample to exclude the smallest and largest cities (2.5% in each case) according to population records in 1970. We note that our qualitative and quantitative findings remain largely unaffected by these changes. Finally, in Columns (5)–(8), we repeat the analysis by dropping one climatic region at a time. As the table shows the direction of our results prevails, although we lose statistical significance in some cases due to smaller samples.

In Table 6 we adopt a similar procedure to examine the robustness of our results for the full sample of cities. Once again, we find that the various alternative specifications produce fairly similar results to the baseline results reported earlier.

5.3 Relation with Existing Estimates

This paper is the first to provide a comprehensive empirical analysis of how local labor markets respond to large and persistent rainfall shortages, and to tie the resulting estimates to recent developments in the spatial general-equilibrium theory. Therefore, it is important to verify the extent to which our findings are consistent with previous research that used different empirical strategies to estimate the effects of climate shocks on a more limited set of labor market outcomes than those examined here.

A strand of existing research examines wage effects of rainfall shortages. Using data from three independent cross-sectional household surveys conducted in Brazil during the period 1992–1995, Mueller and Osgood (2009) find that past occurrences of droughts in a given federal state have persistent negative wage effects. For India, Jayachandran (2006) finds that negative shocks to agricultural productivity (as measured by rainfall shocks) have negative impacts on wages, and shows that these impacts are stronger for workers that are poorer, less able to migrate, and more credit-constrained (because such workers have a more inelastic labor supply). These findings are generally in line with the long-run wage effects we document.

A related body of work examines the impact of climate shocks on migration flows and local demographics. Hornbeck (2012) finds that the American Dust Bowl, an environmental catastrophe that eroded vast areas of the US, led to a reduction in revenues and in land values in the short-run, and to population decline in the long term. Dinkelman (2013) shows that short-run out-migration is more responsive to drought in South African regions characterized by lower mobility restrictions. These results are consistent with the long-term effects of drought on migration patterns we document in this paper. Our findings about migration patterns in response to drought are also compatible with Sahota (1968), who finds that inter-state migration in Brazil is highly responsive to earning differentials.

6 Concluding Remarks

We have documented the long-run impacts of droughts on local labor markets in Brazil. By exploiting rainfall data spanning over a century, we have constructed contemporaneous and historical drought indices for more than 3,000 local communities. Using these measures in conjunction with five waves of population census data in a difference-in-differences design, we found that a higher frequency of drought reduces local value added, employment and wages in the agricultural sector; causes job losses and depresses wages in local manufacturing and services; and induces out-migration, especially among younger cohorts and men, leading to relative population decline.

The evidence we provide lends support to growing concerns about potentially large distributional effects of climate change within countries. As extreme weather events become more frequent, drought-prone areas are likely to suffer from progressive decline of employment in both tradable and non-tradable industries, while population moves elsewhere. Workers choosing to stay behind in these areas will tend to be older and receive lower levels of pay for a given level of education. On the other hand, areas that receive migrants will have to find effective ways to deal with the implications of rising population, including increased demand for housing and local public services.

From a methodological perspective, the quasi-experimental evidence we offer suggests that recent advances in spatial general-equilibrium theory due to Moretti (2010, 2011) are a powerful framework to predict how local labor markets will adapt to climate change. Estimating the structural parameters of this theory and calibrating them to match key moments of environmental and local labor market data around the world offer a promising route for conducting predictive research in this domain. Additionally, future research may estimate the impacts of climate shocks on housing markets, an aspect that we have not dealt with because of data limitations.

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Table 1. City Mean Characteristics

	Sample	
	Rural	All
	[1]	[2]
Mean 1970		
Log (Agricultural value added)	8.602	8.506
Total population (thousands)	12.282	25.818
Population $<$ 15 years old (% of total)	45.402	44.426
Population 15 to 59 years old (% of total)	49.630	50.375
Population $\geq$ 60 years old (% of total)	4.842	5.064
Skilled population (% of total)	0.476	0.928
Drought (Index) in previous decade	0.110	0.114
Drought (t)	0.264	0.274
Mean trend (change 1960-1970)		
Log (Agricultural value added)	0.701	0.834
Total population	0.006	0.071

Note: Cities are classified as rural if Agricultural GDP / GDP in 1970 was higher than 50%. Skilled individuals are those aged 14-60 with high school education or more. Trend refers to the log change between census years. Source: Authors calculations based on data from Climatic Research Unit (CRU), Instituto de Pesquisa Economica Aplicada (IPEA), Brazil Population Censuses (BPC).

Table 2. Short- and Long-run Effects of Drought (Main)
(1970-2010)

	Rural		All	
	Drought (t)	Drought (Index) in previous decade	Drought (t)	Drought (Index) in previous decade
	[1]	[2]	[3]	[4]
Log (Agricultural value added)	-0.133***	-0.336**	-0.110***	-0.100
	[0.048]	[0.150]	[0.038]	[0.136]
Log (Wages)	-0.007	-0.001	-0.030*	-0.010
	[0.017]	[0.054]	[0.018]	[0.047]
Log (Adjusted Wages)	-0.019*	-0.098***	-0.018*	-0.099***
	[0.010]	[0.023]	[0.009]	[0.029]
Emigration Rate	0.016***	0.061***	0.013***	0.069***
	[0.004]	[0.012]	[0.004]	[0.013]
Immigration Rate	-0.003	-0.003	-0.004	-0.007
	[0.004]	[0.016]	[0.004]	[0.025]
Log (Population)	-0.032***	-0.156***	-0.031***	-0.148***
	[0.009]	[0.040]	[0.008]	[0.037]
Log (Jobs)	-0.011	-0.195***	0.012	-0.117*
	[0.016]	[0.059]	[0.017]	[0.060]
Income Index	-0.046**	-0.136*	-0.136***	-0.028
	[0.021]	[0.069]	[0.026]	[0.059]
Observations	7,280	7,280	14,560	14,560

Note: Entries in each row of columns 1 and 2 (columns 3 and 4) are point estimates from a separate regression using data on rural (all) cities. Each regression includes the contemporaneous drought indicator (Dsct) and the historical drought index (Hsct). All models are estimated in log changes and include city and climatic region-year fixed-effects. Jobs and wages are those of males aged 15-59 years old. The income index is the income component of the human development indicator published by IPEA and is available for 1970-2000. The classification of individuals in emigrants or immigrants is determined by the city of residence 5 years ago. Emigration rate (t) = Emigrants in decade (t) / Population in decade (t-1). Immigration rate (t) = Immigrants in decade (t) / Population in decade (t-1). Cities are classified as rural if Agricultural GDP / GDP ratio in 1970 was equal or above 50%. Standard errors, clustered by latitude and longitude of the city, are reported in brackets. * significant at 10% level, ** significant at 5% level, *** significant at 1% level. Source: Authors calculations based on data from Climatic Research Unit (CRU), Instituto de Pesquisa Economica Aplicada (IPEA), Brazil Population Censuses (BPC).

Table 3. Short- and Long-Run Effects of Droughts (Wages and Jobs by Sector) (1970-2010)

	Rural		All	
	Drought (t)	Drought (Index) in previous decade	Drought (t)	Drought (Index) in previous decade
	[1]	[2]	[3]	[4]
Log (Wages)				
Agriculture	-0.025	-0.058	-0.064***	-0.024
	[0.021]	[0.066]	[0.023]	[0.057]
Manufacturing	-0.036**	0.040	-0.048***	-0.066
	[0.017]	[0.062]	[0.013]	[0.057]
Services	0.006	-0.097*	-0.031**	-0.145***
	[0.021]	[0.056]	[0.014]	[0.042]
Log (Adjusted Wages)				
Agriculture	-0.037***	-0.101***	-0.046***	-0.082***
	[0.010]	[0.021]	[0.010]	[0.027]
Manufacturing	-0.004	-0.064**	-0.003	-0.090***
	[0.011]	[0.030]	[0.009]	[0.032]
Services	-0.019**	-0.091***	-0.023***	-0.096***
	[0.008]	[0.023]	[0.008]	[0.027]
Log (Jobs)				
Agriculture	0.003	-0.280***	-0.004	-0.209***
	[0.027]	[0.069]	[0.029]	[0.063]
Manufacturing	-0.077*	-0.267**	-0.050*	-0.200**
	[0.043]	[0.125]	[0.029]	[0.098]
Services	-0.032	-0.104*	-0.020	-0.036
	[0.023]	[0.061]	[0.015]	[0.045]
Observations	6,816	6,816	13,884	13,884

Note: Entries in each row of columns 1 and 2 (columns 3 and 4) are point estimates from a separate regression using data on rural (all) cities. Each regression includes the contemporaneous drought indicator (Dsct) and the historical drought index (Hsct). All models are estimated in log changes and include city and climatic region-year fixed-effects. Jobs and wages are those of males aged 15-59 years old. Cities are classified as rural if Agricultural GDP / GDP ratio in 1970 was equal or above 50%. Standard errors, clustered by latitude and longitude of the city, are reported in brackets. * significant at 10% level, ** significant at 5% level, *** significant at 1% level. Source: Authors calculations based on data from Climatic Research Unit (CRU), Instituto de Pesquisa Economica Aplicada (IPEA), Brazil Population Censuses (BPC).

Table 4. Short- and Long-Run Effects of Drought (Migration)
(1970-2010)

	Rural		All	
	Drought (t)	Drought (Index) in previous decade	Drought (t)	Drought (Index) in previous decade
	[1]	[2]	[3]	[4]
Emigration Rate				
Age less than 15	0.007***	0.035***	0.005**	0.039***
	[0.002]	[0.007]	[0.002]	[0.007]
15 to 59	0.008***	0.024***	0.008***	0.028***
	[0.002]	[0.005]	[0.002]	[0.005]
60 or more	0.000	0.002***	0.000	0.002***
	[0.000]	[0.000]	[0.000]	[0.000]
Male	0.008***	0.030***	0.006***	0.034***
	[0.002]	[0.006]	[0.002]	[0.006]
Singles	0.005***	0.034***	0.004***	0.037***
	[0.002]	[0.005]	[0.002]	[0.005]
Unskilled	0.006***	0.012***	0.007***	0.010***
	[0.002]	[0.004]	[0.002]	[0.004]
Skilled	0.006***	0.025***	0.005***	0.034***
	[0.002]	[0.004]	[0.002]	[0.004]
Non-white	0.008***	0.039***	0.005*	0.039***
	[0.003]	[0.008]	[0.003]	[0.007]
White	0.008***	0.021***	0.008***	0.028***
	[0.002]	[0.006]	[0.002]	[0.007]
Immigration Rate				
Age less than 15	-0.001	-0.001	-0.002	-0.003
	[0.002]	[0.009]	[0.002]	[0.012]
15 to 59	-0.002	-0.001	-0.002	-0.004
	[0.002]	[0.007]	[0.002]	[0.012]
60 or more	0.000	-0.001***	0.000	-0.001
	[0.000]	[0.000]	[0.000]	[0.001]
Male	-0.001	0.000	-0.002	-0.002
	[0.002]	[0.008]	[0.002]	[0.013]
Singles	-0.003**	0.005	-0.002*	0.006
	[0.001]	[0.005]	[0.001]	[0.007]
Unskilled	-0.005***	-0.008	-0.009***	-0.013*
	[0.002]	[0.007]	[0.002]	[0.007]
Skilled	0.002	0.005	0.004***	0.005
	[0.001]	[0.005]	[0.002]	[0.013]
Non-white	-0.005	-0.004	-0.006***	-0.008
	[0.004]	[0.012]	[0.002]	[0.013]
White	0.002	-0.001	0.001	-0.003
	[0.002]	[0.008]	[0.002]	[0.016]
Observations	7,044	7,044	14,183	14,183

Note: Entries in each row of columns 1 and 2 (columns 3 and 4) are point estimates from a separate regression using data on rural (all) cities. Each regression includes the contemporaneous drought indicator (Dsct) and the historical drought index (Hsct). All models are estimated in log changes and include city and climatic region-year fixed-effects. Classification of individuals in emigrants or immigrants is determined by city of residence 5 years ago. Emigration rate (t) = Emigrants in decade (t) / Population in decade (t-1). Immigration rate (t) = Immigrants in decade (t) / Population in decade (t-1). Skilled individuals are those aged 14-60 with high school education or more. Unskilled are individuals aged 14-60 with no high school education or less. Non-white includes black, asian and indigenous races. Cities are classified as rural if Agricultural GDP / GDP ratio in 1970 was equal or above 50%.Standard errors, clustered by latitude and longitude of the city, are reported in brackets. * significant at 10% level, ** significant at 5% level, *** significant at 1% level. Source: Authors calculations based on data from Climatic Research Unit (CRU), Instituto de Pesquisa Economica Aplicada (IPEA), Brazil Population Censuses (BPC).

Table 5. Robustness Rural Municipalities

		Full sample (Baseline) [1]	HDI (0.05) [2]	HDI (0.25) [3]	No extremes [4]	No Clim. Region 1 [5]	No Clim. Region 2 [6]	No Clim. Region 3 [7]	No Clim. Region 4 [8]
Log(Agricultural value added)	Drought (t)	-0.133***	-0.135***	-0.129***	-0.122***	-0.176***	-0.076	-0.154***	-0.117**
		[0.048]	[0.048]	[0.047]	[0.047]	[0.052]	[0.060]	[0.050]	[0.055]
	Drought (Index) in previous decade	-0.336**	-0.293**	-0.380**	-0.338**	-0.426***	-0.464***	-0.180	-0.263
		[0.150]	[0.135]	[0.178]	[0.146]	[0.160]	[0.163]	[0.155]	[0.211]
Log(Wages)	Drought (t)	-0.007	-0.006	-0.008	-0.007	-0.030	-0.011	-0.013	0.030
		[0.017]	[0.017]	[0.017]	[0.017]	[0.019]	[0.024]	[0.018]	[0.019]
	Drought (Index) in previous decade	-0.001	0.008	-0.026	-0.002	-0.102*	0.045	0.015	0.046
		[0.054]	[0.050]	[0.064]	[0.055]	[0.060]	[0.065]	[0.066]	[0.069]
Log(Adjusted Wages)	Drought (t)	-0.019*	-0.018*	-0.019*	-0.020*	-0.022**	-0.004	-0.024**	-0.021
		[0.010]	[0.010]	[0.010]	[0.010]	[0.011]	[0.010]	[0.011]	[0.013]
	Drought (Index) in previous decade	-0.098***	-0.071***	-0.153***	-0.097***	-0.139***	-0.028	-0.107***	-0.112***
		[0.023]	[0.020]	[0.032]	[0.023]	[0.025]	[0.021]	[0.030]	[0.032]
Emigration Rate	Drought (t)	0.016***	0.016***	0.015***	0.017***	0.023***	-0.002	0.017***	0.020***
		[0.004]	[0.004]	[0.004]	[0.004]	[0.005]	[0.004]	[0.005]	[0.005]
	Drought (Index) in previous decade	0.061***	0.052***	0.077***	0.062***	0.073***	0.044***	0.064***	0.054***
		[0.012]	[0.012]	[0.015]	[0.013]	[0.014]	[0.012]	[0.015]	[0.015]
Immigration Rate	Drought (t)	-0.003	-0.003	-0.002	-0.001	0.001	-0.011**	-0.001	-0.001
		[0.004]	[0.004]	[0.004]	[0.004]	[0.005]	[0.005]	[0.005]	[0.006]
	Drought (Index) in previous decade	-0.003	-0.008	0.008	0.003	0.007	-0.007	0.005	-0.026
		[0.016]	[0.014]	[0.020]	[0.012]	[0.014]	[0.020]	[0.015]	[0.019]
Log(Population)	Drought (t)	-0.032***	-0.034***	-0.029***	-0.030***	-0.038***	-0.030***	-0.026***	-0.035***
		[0.009]	[0.009]	[0.009]	[0.009]	[0.012]	[0.011]	[0.010]	[0.010]
	Drought (Index) in previous decade	-0.156***	-0.157***	-0.136***	-0.149***	-0.169***	-0.151***	-0.191***	-0.104***
		[0.040]	[0.036]	[0.046]	[0.039]	[0.045]	[0.045]	[0.044]	[0.041]
Log(Jobs)	Drought (t)	-0.011	-0.011	-0.008	-0.011	-0.022	-0.022	0.009	-0.014
		[0.016]	[0.017]	[0.016]	[0.016]	[0.020]	[0.020]	[0.018]	[0.019]
	Drought (Index) in previous decade	-0.195***	-0.162***	-0.249***	-0.201***	-0.171***	-0.250***	-0.192***	-0.172**
		[0.059]	[0.056]	[0.067]	[0.055]	[0.060]	[0.061]	[0.068]	[0.079]
Income index	Drought (t)	-0.046**	-0.047**	-0.043**	-0.041*	-0.073***	-0.023	-0.046**	-0.039
		[0.021]	[0.021]	[0.021]	[0.021]	[0.026]	[0.027]	[0.022]	[0.025]
	Drought (Index) in previous decade	-0.136*	-0.100	-0.210***	-0.141**	-0.146*	-0.109	-0.124	-0.154*
		[0.069]	[0.066]	[0.077]	[0.069]	[0.079]	[0.071]	[0.077]	[0.080]
	Observations	7280	7280	7280	7082	5696	4644	5744	5756

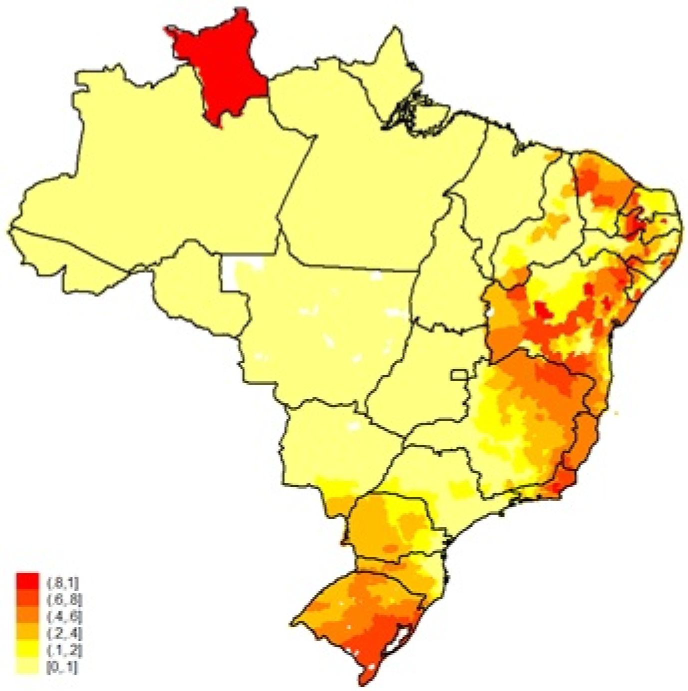
Note: Entries for each column/outcome are points estimates from a separate regression. Each regression includes the contemporaneous drought indicator (Dsct) and the historical drought index (Hsct). All models are estimated in log changes and include city and climatic region-year fixed-effects. Jobs and wages are those of males 15-59 years old. Classification of individuals in emigrants or immigrants determined by city of residence 5 years ago. Emigration rate (t) = Emigrants in decade (t) / Population in decade (t-1). Immigration rate (t) = Immigrants in decade (t) / Population in decade (t-1). Cities are classified as rural if Agricultural GDP / GDP ratio in 1970 was equal or above 50%. No extremes only includes cities with population greater than the percentile 2.5 and lower than percentile 97.5 in year 1970. Climate regions are an aggregated version of the Kppen-geiger climate classification. Further information can be found in http://koeppen-geiger.vu-wien.ac.at/shifts.htm . Climate region 1 include tropical rainforest, monsoon and tropical wet and dry climate with dry season. Climate region 2 include tropical wet and dry climate. Climate region 3 include arid (steppe and hot) and temperate (with dry winter and hot summer). Climate region 4 include temperate without dry season (with hot summer and warm summer) and temperate with dry winter and warm summer. Standard errors clustered by latitude and longitude of the city. * significant at 10% level, ** significant at 5% level, *** significant at 1% level. Source: Authors calculations based on data from Climatic Research Unit (CRU), Instituto de Pesquisa Economica Aplicada (IPEA), Brazil Population Censuses (BPC).

Table 6. Robustness: All Municipalities

		Full sample (Baseline) [1]	HDI (0.05) [2]	HDI (0.25) [3]	No extremes [4]	No Clim. Region 1 [5]	No Clim. Region 2 [6]	No Clim. Region 3 [7]	No Clim. Region 4 [8]
Log(Agricultural GDP)	Drought (t)	-0.110***	-0.111***	-0.108***	-0.109***	-0.125***	-0.061	-0.108***	-0.139***
		[0.038]	[0.038]	[0.038]	[0.036]	[0.042]	[0.048]	[0.041]	[0.045]
	Drought (Index) in previous dacade	-0.100	-0.105	-0.069	-0.084	-0.133	-0.127	0.011	-0.156
		[0.136]	[0.124]	[0.160]	[0.132]	[0.151]	[0.147]	[0.137]	[0.186]
Log(Wages)	Drought (t)	-0.030*	-0.030*	-0.031*	-0.031*	-0.056***	-0.049*	-0.035*	0.024
		[0.018]	[0.018]	[0.018]	[0.018]	[0.019]	[0.025]	[0.019]	[0.015]
	Drought (Index) in previous dacade	-0.01	-0.002	-0.025	-0.012	-0.07	0.01	0.014	-0.003
		[0.047]	[0.043]	[0.056]	[0.047]	[0.057]	[0.056]	[0.058]	[0.059]
Log(Adj. Wages)	Drought (t)	-0.018*	-0.017*	-0.018*	-0.019**	-0.025**	-0.013	-0.024***	-0.003
		[0.009]	[0.009]	[0.009]	[0.009]	[0.011]	[0.011]	[0.010]	[0.011]
	Drought (Index) in previous dacade	-0.099***	-0.070***	-0.160***	-0.095***	-0.122***	-0.012	-0.112***	-0.164***
		[0.029]	[0.026]	[0.037]	[0.028]	[0.036]	[0.031]	[0.036]	[0.036]
Emigration Rate	Drought (t)	0.013***	0.013***	0.012***	0.014***	0.019***	-0.002	0.013***	0.018***
		[0.004]	[0.004]	[0.004]	[0.004]	[0.005]	[0.004]	[0.005]	[0.005]
	Drought (Index) in previous dacade	0.069***	0.058***	0.087***	0.069***	0.083***	0.053***	0.072***	0.058***
		[0.013]	[0.011]	[0.015]	[0.013]	[0.014]	[0.012]	[0.014]	[0.015]
Immigration Rate	Drought (t)	-0.004	-0.004	-0.004	-0.003	-0.002	-0.011***	-0.003	-0.001
		[0.004]	[0.004]	[0.004]	[0.004]	[0.005]	[0.005]	[0.004]	[0.004]
	Drought (Index) in previous dacade	-0.007	-0.008	-0.004	-0.003	0.000	-0.019	-0.004	-0.01
		[0.025]	[0.022]	[0.028]	[0.024]	[0.029]	[0.030]	[0.027]	[0.022]
Log(Population)	Drought (t)	-0.031***	-0.032***	-0.029***	-0.033***	-0.036***	-0.032***	-0.029***	-0.030***
		[0.008]	[0.008]	[0.008]	[0.008]	[0.010]	[0.011]	[0.009]	[0.008]
	Drought (Index) in previous dacade	-0.148***	-0.142***	-0.146***	-0.147***	-0.158***	-0.149***	-0.169***	-0.109***
		[0.037]	[0.033]	[0.044]	[0.037]	[0.044]	[0.046]	[0.042]	[0.032]
Log(Jobs)	Drought (t)	0.012	0.012	0.013	0.007	0.006	-0.016	0.032	0.015
		[0.017]	[0.018]	[0.017]	[0.017]	[0.020]	[0.018]	[0.020]	[0.023]
	Drought (Index) in previous dacade	-0.117*	-0.089	-0.167***	-0.128**	-0.104	-0.208***	-0.084	-0.082
		[0.060]	[0.060]	[0.062]	[0.059]	[0.066]	[0.064]	[0.070]	[0.080]
Income index	Drought (t)	-0.136***	-0.136***	-0.136***	-0.124***	-0.167***	-0.108***	-0.132***	-0.135***
		[0.026]	[0.025]	[0.026]	[0.025]	[0.027]	[0.028]	[0.024]	[0.037]
	Drought (Index) in previous dacade	-0.028	-0.020	-0.047	-0.048	-0.018	0.011	-0.009	-0.094
		[0.059]	[0.055]	[0.066]	[0.059]	[0.071]	[0.065]	[0.068]	[0.064]
	Observations	14560	14560	14560	13830	11660	9188	12020	10812

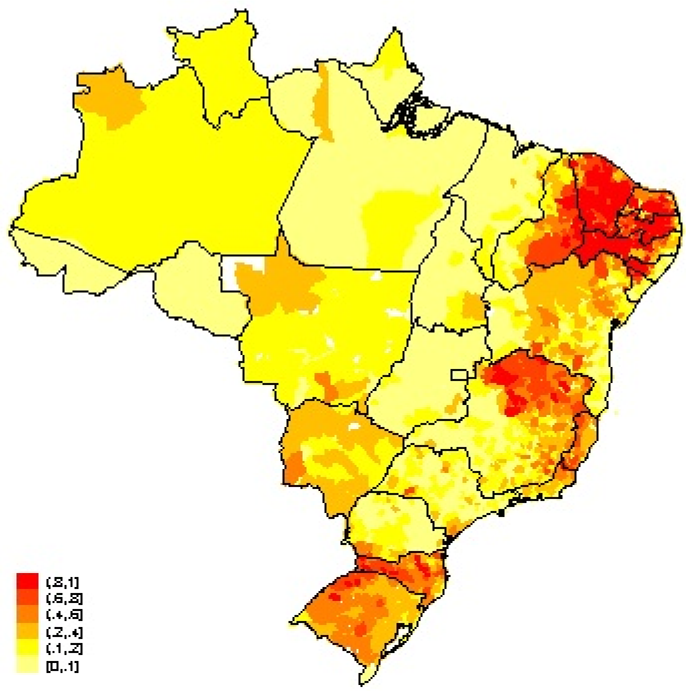
Note: Entries for each column/outcome are points estimates from a separate regression. Each regression includes the contemporaneous drought indicator (Dsct) and the historical drought index (Hsct). All models are estimated in log changes and include city and climatic region-year fixed-effects. Jobs and wages are those of males 15-59 years old. Classification of individuals in emigrants or immigrants determined by city of residence 5 years ago. Emigration rate (t) = Emigrants in decade (t) / Population in decade (t-1). Immigration rate (t) = Immigrants in decade (t) / Population in decade (t-1). No extremes only includes cities with population greater than the percentile 2.5 and lower than percentile 97.5 in year 1970. Climate regions are an aggregated version of the Kppen-geiger climate classification. Further information can be found in http://koeppen-geiger.vu-wien.ac.at/shifts.htm . Climate region 1 include tropical rainforest, monsoon and tropical wet and dry climate with dry season. Climate region 2 include tropical wet and dry climate. Climate region 3 include arid (steppe and hot) and temperate (with dry winter and hot summer). Climate region 4 include temperate without dry season (with hot summer and warm summer) and temperate with dry winter and warm summer. Standard errors clustered by latitude and longitude of the city. * significant at 10% level, ** significant at 5% level, *** significant at 1% level. Source: Authors calculations based on data from Climatic Research Unit (CRU), Instituto de Pesquisa Economica Aplicada (IPEA), Brazil Population Censuses (BPC).

Figure 1. Spatial Distribution of Weather-Based Drought Indicators 1970-2010



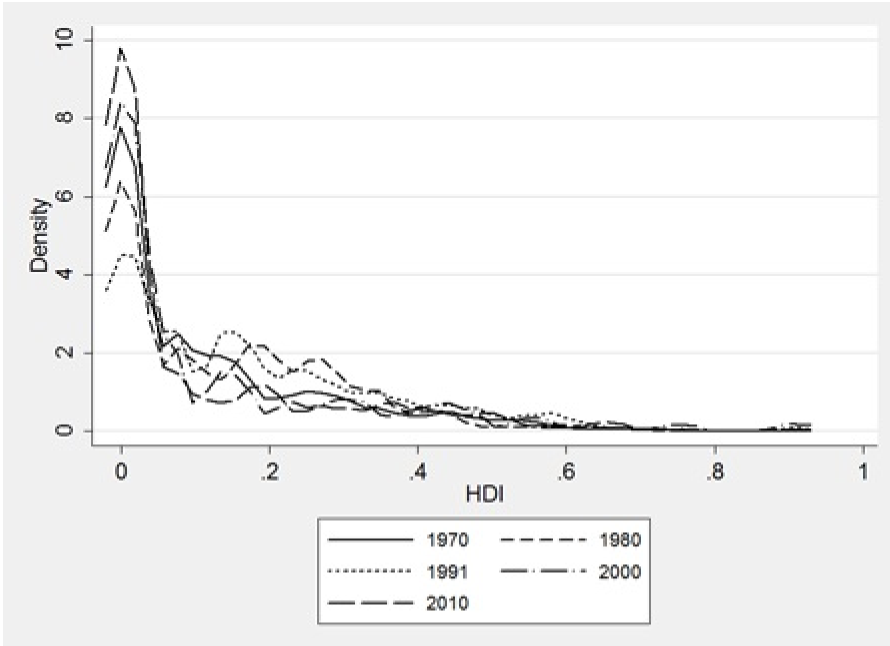
Source: Authors calculations based on data from Climatic Research Unit (CRU), Instituto de Pesquisa Economica Aplicada (IPEA).

Figure 2. Spatial Distribution of Emergency Declarations Due to Drought 2003-2008



Source: Authors calculations based on data from the National Secretariat of Civil Defence (NSCD).

Figure 3. Distribution of Historical Drought Index



Source: Authors calculations based on data from Climatic Research Unit (CRU), Instituto de Pesquisa Economica Aplicada (IPEA).