The Effects of Climate Change on Labor and Capital Reallocation

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Abstract

Climate change is expected to reduce agricultural productivity in developing countries. Potential adaptation paths include the reallocation of capital and labor towards non-agricultural sectors or other regions. We study the experience of Brazil to provide direct evidence on these mechanisms. We document that local economies insure themselves against weather fluctuations via financial integration with other regions. However, regions subject to persistent increases in dryness relative to historical averages experience large capital and labor outflows. Dryness affects the structure of both the local economy and that of destination regions where referral networks direct climate migrants to small firms outside of manufacturing.

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I Introduction

The speed of climate change is one of the major challenges of our time. As average temperatures rise in many regions around the globe, the frequency and intensity of extreme weather events, such as droughts and floods, has increased (IPCC, 2021). Developing economies are particularly exposed to these events because they tend to be located in tropical areas and a significant share of their population is still employed in agriculture. Potential adjustment mechanisms include the reallocation of economic activity towards non-agricultural sectors or towards other regions. However, there is scarce direct empirical evidence on these mechanisms and the extent to which they are shaped by factor market integration. In this paper, we study the effects of recent changes in climate in Brazil on labor and capital allocation across regions, sectors and firms.

Brazil's climate has already started experiencing the effects of global warming highlighted by climate science. The IPCC reports that the signal of climate change emerged in Brazil around the 1980s, when temperature changes started to be two standard deviations above natural year-to-year variations.[1] Since then, warming trends have accelerated with average temperature increasing 1°C between 1980 and 2020. Climate science also predicts that global warming leads to heterogeneous effects on average rainfall patterns across the earth. In the case of Brazil, climate models predict a reduction in precipitation in almost all regions.[2] Both higher temperatures and lower precipitation are expected to lead to worsening drought conditions. Indeed, we document that Brazil experienced an increase in the frequency of droughts between 2000 and 2020, using newly digitized administrative data from the National System of Civil Protection in Brazil (SINPDEC). In addition, we document an increase in average excess dryness using the Standardized Precipitation and Evapotranspiration Index (SPEI), which measures the moisture deficit in a given location relative to its 100 year average and is based on local precipitation and temperature data (Vicente-Serrano et al., 2010).

We use the SPEI index to study factor market adjustment to both temporary and persistent increases in dryness. Because this index captures *deviations* in meteorological conditions relative to the past century, it is well suited to study the effects of climate change. In addition, we show that SPEI is a strong predictor of the drought events reported in the administrative civil protection data (SINPDEC). First, we exploit year-to-year changes in SPEI to study the short run response to extreme weather events. Note that climate science cannot attribute particular extreme weather events to global warming.

[1] The IPCC 2021 report highlights that the signal of climate change, namely temperature changes being two standard deviations above year-to-year variations in the baseline period 1850-1900, emerged earlier in tropical areas. This is because regions in high latitudes are expected to experience larger temperature increases than regions at lower latitudes but natural variations in temperature are also much larger at high latitudes. For a detailed discussion, see pages 133 and 246 of IPCC (2021).

[2] Climate models predict that global warming will increase precipitation in high and low latitudes but decrease it in middle ones (IPCC 2021, page 645).

Still, factor flows in response to this yearly measure can give information on the potential adjustment to climate change to the extent that it increases the probability of each of these events. Second, we take decadal averages of the SPEI index in an attempt to capture persistent increases in dryness in line with the climate science prediction that global warming leads to lower average precipitation in Brazil. These decadal excess dryness measures show large variation in drought conditions across regions and time in Brazil, which permits to construct a differences-in-differences empirical strategy to identify the effects of changes in dryness on factor allocation. We identify effects on local labor and capital markets by comparing outcomes across municipalities differently affected by excess dryness. In turn, we measure spillover effects by tracking capital and labor flows to other municipalities whose factor markets are integrated with areas suffering excess dryness.

We combine the meteorological data discussed above with detailed measures of agricultural output, capital and labor flows across sectors, regions and firms. First, we use PAM for municipality-level data on area planted, area harvested and agricultural output. Second, we use balance sheet data from all bank branches in Brazil (ESTBAN) to track capital flows across municipalities and to construct a measure of capital market integration across municipalities using the structure of bank branch networks. This measure is based on the assumption that two municipalities are more financially integrated if they both have branches of the same bank, which would be the case if there is any friction in the interbank market that banks solve through internal capital markets. Third, we use the Population Census, which permits to track regional migration flows as it records the municipality of origin of all internal migrants in Brazil. We use this information to construct a measure of labor market integration across municipalities using past migrant networks. Finally, we use social security data from the Annual Social Information System (RAIS), which permits to track workers across regions, sectors and firms to construct a firm-level measure of labor market integration with each potential origin region using the employment histories of migrant workers.

As expected, we find that regions subject to abnormally dry meteorological conditions in a given year experience a reduction in agricultural output. In particular, municipalities moving from the median to the 90th percentile of excess dryness experience a reduction of agricultural output of 6%. This reduction is highly non-linear with losses abruptly increasing to an average of 16% in the top decile. We also estimate the effects of experiencing two full decades of excess dryness relative to historical averages. We find that a municipality moving from the median to the 90th percentile experiences a 22.5% reduction in agricultural output. This sharp reduction in output suggests a limited scope for adaptation responses within the agricultural sector such as the adoption of new technologies or crops. Then, in what follows, we focus on measuring the relative importance of factor reallocation across sectors and regions as adaptation mechanisms.

First, we study the role of capital flows across municipalities as a means to adjust to both single-year drought events and persistent increases in dryness. We show that there is an 8 percent increase in loans to agriculture in municipalities experiencing a dry year. These loans are funded by capital inflows coming from other regions connected through the bank branch network. This suggests that local economies are able to partially insure themselves against negative weather shocks by being financially integrated with other regions. However, when we analyze the impact of a full decade of excess dryness relative to historical averages, we find that affected regions experience capital outflows, driven by a reduction in lending. More specifically, a municipality moving from the median to the 90th percentile of average excess dryness over the 2001 to 2010 period experiences an 11.8 percent decline in lending originated by local branches to all sectors of the economy. This is consistent with the idea that a full decade of unusually dry meteorological conditions has (or is perceived to have) permanent negative effects on local agricultural productivity, thus capital reallocates away from affected regions. In addition, we find negative spillover effects on municipalities financially integrated with areas experiencing persistent droughts. These municipalities also experience capital outflows and a sharp reduction in loans to all sectors. Note that banks in these municipalities were the ones providing insurance in the short run, thus they are likely to be exposed to a reduction in liquidity due to both higher loan defaults and lower savings deposits in their branches located in areas subject to droughts.

Second, we study the impact of excess dryness on labor reallocation. We find that a municipality moving from the median to the 90th percentile of decadal excess dryness relative to historical averages experiences a sharp reduction in decadal employment in both agriculture (-7.3%) and services (-5.5%) but an increase in manufacturing employment (5.7%). These changes in the structure of the local economy are consistent with a classic small open economy model where agriculture and manufacturing are tradable sectors, and services are non tradable (Corden and Neary, 1982). In this model, a reduction in agricultural productivity shifts comparative advantage towards manufacturing but reduces demand for local non-traded goods such as services. Still, only a third of displaced workers are absorbed by local manufacturing: we document large net out-migration flows from affected areas. As a result, a municipality moving from the median to the 90th percentile of decadal excess dryness experiences a 5.2 percent reduction in population.

The documented large reductions in loans (11.8%) and population (5.2%) in municipalities subject to a full decade of excess dryness suggest a limited scope for local adaptation by reallocating capital and labor towards local traded sectors less affected by climatic conditions such as manufacturing. In addition, note that the estimates imply a reduction in loans per capita in affected regions, which can limit adaptation opportunities by constraining investment in new activities.

Next, we trace labor reallocation towards other regions. We start by investigating the effect of climate migrants on the structure of the economy of destination regions. For this purpose, we measure labor market integration across regions using past migration flows. We construct a measure of indirect labor market exposure of each destination municipality to persistent droughts by summing excess dryness in each potential origin, weighted by the share of all migrants in that destination who came from that particular origin in previous waves of the decadal Population Census. To account for spatial correlation in climatic conditions, we exclude from our measures of indirect exposure those areas that are within a 55km radius from a given municipality and cluster standard errors at larger geographical units. We find that municipalities more exposed to excess dryness via migration links experience a larger increase in net in-migration, which is primarily driven by higher inflows rather than lower outflows. In addition, we document that these regions expand employment in agriculture and services, but not in manufacturing.

The findings discussed above suggest that when agricultural workers who lost their jobs due to excess dryness stay in their region of origin, they tend to find jobs in the local manufacturing sector. However, when they migrate to other regions they are more likely to find jobs in agriculture or services. This finding might be driven by the fact that climate migrants lack the skills required for employment in manufacturing in major destination regions. In this case, the absence of migrant reallocation into manufacturing would reflect an optimal allocation of labor at destination. Alternatively, this finding could also be driven by the fact that migrants' social networks are disconnected from manufacturing firms at destination. This asymmetry in labor market frictions across sectors would result in labor misallocation. We turn to explore these two potential explanations next.

To shed light on the assignment process of climate migrants to jobs at destination, we use the social security data and bring the analysis to the firm-level. For each firm, we construct a measure of exposure to climate migrants. We measure whether a firm is connected to regions experiencing excess dryness through social networks by computing its baseline share of workers who came in the past from origins which would experience high excess dryness. We find that workers from areas experiencing excess dryness tend to reallocate towards firms which already had a large share of migrants from those origins. This implies that climate migrants do not amount to a symmetric increase in labor supply for all firms. Instead, referral networks direct migrants to connected firms. This has important implications for the composition of economic activity in destination regions because connected firms are more likely to be small and outside of manufacturing, as we document below.

First, we find that the manufacturing sector is the least connected to areas characterized by higher excess dryness through past migrant networks: in the baseline period, only about 2 percent of its workers came from those areas compared to 4 percent in services and 6 percent in agriculture. This lower labor market integration of manufacturing firms with regions affected by droughts is at first sight surprising because deviations in excess dryness are "as good as randomly assigned" in the sense that they are uncorrelated with initial characteristics of municipalities such as income per-capita or urbanization. On further inspection, the lower cross-regional labor market integration of manufacturing is explained by the fact that manufacturing is geographically concentrated due to agglomeration economies. Second, in a given destination, firms in the agricultural and services sector display a larger employment elasticity to labor supply shocks driven by climate migrants from connected origins. This implies that, even in the presence of referral networks, manufacturing firms are less prone to employ migrants pushed by excess dryness. This might be due to the fact that manufacturing firms require specialized skills that are sourced in thick local labor markets. Third, we find that the estimated elasticity of worker inflows from connected origins experiencing higher excess dryness is larger for small than for large firms. Hence, climate migrants affect the shape of the firm-size distribution, increasing the weight of small firms, which tend to pay lower wages and display lower productivity.[3]

Finally, let us emphasize that higher excess dryness relative to historical averages in some locations can have effects in other locations through several channels other than labor and capital flows. For example, goods trade can generate demand or supply linkages across regions. To control for these linkages, we construct a measure of exposure to excess dryness via trade links in the spirit of the market access measure of Donaldson and Hornbeck (2016). In particular, this measure is obtained by summing up excess dryness across all locations, weighted by the trade costs computed based on travel time via the highway network of Brazil. We find that controlling for this exposure via trade links leaves our estimates of labor and capital market links unaffected and that the measure itself has no significant effects on capital flows or employment changes. In addition, our firm-level results are robust to this concern because we can track workers across regions and firms in the social security data. This permits to absorb aggregate firm growth at each destination municipality, which controls for any general equilibrium effects of droughts in connected areas. In addition, we can compare worker flows from drought origins with worker flows from other areas at the firm level in each destination. This permits to separate the labor market effects of droughts on connected firms from other effects taking place through the goods or capital markets. This is because product demand or capital supply linkages affecting firm growth should affect labor demand from all origins.

Related Literature

This paper builds on the empirical literature studying the effects of both temporary weather shocks and persistent changes in temperature on economic outcomes, reviewed by Dell et al. (2014). We contribute to this literature by i) measuring capital flows in addition to labor flows, ii) estimating not only local effects but also spillover effects on

[3]For a survey of the evidence on the large-firm wage premium see Oi and Idson (1999). Theories of the firm predict that this premium should capture, at least in part, differences in productivity (Lucas, 1978; Melitz, 2003).

destination regions, and iii) tracking climate migrants across regions, sectors and firms using social security data. Studying how climate change simultaneously affects labor and capital allocation both across regions and sectors paints a more comprehensive picture on the relative importance of potential adaptation mechanisms and how they are shaped by factor market integration.

Empirical studies on the effects of weather shocks on labor markets show that they can generate migration away from affected areas (Jayachandran, 2006; Hornbeck, 2012).[4] Some recent studies have focused on the impact of weather shocks on labor reallocation across sectors, and in particular on the ability of non-agricultural sectors to absorb displaced agricultural workers. For example, Colmer (2021) finds evidence that short-run weather shocks reduce agricultural productivity and generate worker reallocation from agriculture into both manufacturing and services within the same district, but no out-migration. In turn, Henderson et al. (2017) studies the negative impact of long-run changes in moisture on agricultural productivity in Sub Saharan Africa, documenting that only areas with an export-oriented manufacturing sector are able to absorb displaced agricultural workers.[5] Overall, the literature has focused on the local labor market effects of climate shocks. We contribute to this literature by tracking climate migrants across regions and providing direct empirical evidence on the spillover effects of local shocks into other regions integrated through labor markets. In addition, we estimate the response of capital flows across sectors and regions using micro data on lending and deposits which, to the best of our knowledge, had not been previously studied.

A few empirical studies have focused on how market integration shapes the response of local economic outcomes to weather shocks. Jayachandran (2006) finds that wages fluctuate more in response to weather shocks in Indian districts with fewer banks or higher migration costs. Consistently, Burgess and Donaldson (2010) find that local rainfall shortages were less likely to cause famines in colonial India after railroad access increased trade openness. More recently, Allen and Atkin (2022) show that expansions of the Indian highway network reduced the responsiveness of local prices to local rainfall but increased the responsiveness of local prices to yields elsewhere so that farmers shifted their production towards crops with less volatile yields. We contribute to this literature by i) showing how the effects of persistent changes in dryness can be different from those of temporary weather shocks, and ii) tracking spillovers to non-agricultural sectors and other regions by directly measuring labor and capital flows.

In terms of methodology, our paper builds on the literature studying the effects of regional shocks. A first strand of this literature has analyzed the effects of international

[4]However, Boustan et al. (2012, 2020) study the response to natural disasters in the U.S. and find in-migration in response to floods. Their analysis excludes drought events due to endogeneity concerns related to water management practices, as they use administrative data to measure natural disasters.

[5]See also McGuirk and Nunn (2020) on the effects of climate change on the timing of seasonal migration by pastoral groups in Sub Saharan Africa and ensuing conflicts with local farmers.

trade shocks on local labor markets both in India (Topalova, 2010), the U.S. (Autor et al., 2013) and Brazil (Adão, 2015; Dix-Carneiro and Kovak, 2017). These studies find that import competition reduces local wages but does not lead to out-migration. Similarly, Bustos et al. (2019) find no out-migration in response to the adoption of labor-saving GM crops in Brazil. In contrast, in this paper, we find strong migration responses to persistent increases in dryness. One interpretation for this difference in results is that climate change can generate a larger contraction in local labor demand than recent trade or technology shocks.

More recently, the literature has focused on understanding spillover effects of regional shocks building on the market access approach developed by Redding and Venables (2004) and Donaldson and Hornbeck (2016). Adao, Arkolakis, and Esposito (2019) study direct and indirect effects of regional trade shocks in the US. In turn, Bustos, Garber, and Ponticelli (2020) study direct and indirect effects of agricultural productivity growth on capital flows from rural to urban areas in Brazil. Finally, in contemporaneous and independent work, Borusyak et al. (2022) show that empirical estimates of the effects of local labor demand shocks on population which do not take into account the shocks to potential destinations of migrants suffer from attenuation bias whenever shocks are spatially correlated. They propose an economic geography model leading to a specification that combines shocks across locations with information on pre-shock migration connections to capture the relative importance of each potential destination for a locality. They suggest to implement a first order approximation to this equation that corresponds to our empirical strategy to estimate spillovers through labor markets.

Finally, our paper is related to the recent literature proposing quantitative trade and spatial models to estimate the effects of future changes in climate on productivity and spatial allocation of population and economic activity in the very long run (Desmet and Rossi-Hansberg, 2015; Costinot et al., 2016; Balboni, 2019; Conte et al., 2020). In this paper, instead, we focus on changes in climate that have already occurred in the last decades, and study how they affected the reallocation of capital and labor across sectors and space. We think that our estimates based on past experiences of regions affected by changes in climate can be informative on the relative importance of each margin of adjustment considered by quantitative spatial-economic models.

II Background, Data and Identification Strategy

II.A Climate trends in Brazil

Earth's average surface air temperature has increased by about 1°C since 1900, with over half of the increase occurring since the mid-1970s. The IPCC 2021 report highlights that observed changes in temperature have already clearly emerged outside the range of normal variability, relative to 1850-1900 in all land regions with sufficient data (all except Antarctica). As climate has warmed over recent years, a new pattern of more frequent extreme weather events has emerged across the world. Attribution studies show that the warming climate made several recent extreme weather events more likely to happen (Schiermeier, 2018). Warming increases the likelihood of extremely hot days and nights, favours increased atmospheric moisture that may result in more frequent heavy rainfall and snowfall, and leads to evaporation that can exacerbate droughts (National Academies of Sciences, Engineering, and Medicine, 2016).

Expected changes in climate are heterogeneous across geographical areas. Climate model simulations and direct measurements show that high northern latitudes experience the largest long-term warming trends. However, the year-to-year variations in temperature are smallest in the tropics, meaning that the changes there are also apparent, relative to the range of past experiences. As a result, the signal of climate change, defined as temperature change being two-standard deviations above the average in the baseline period 1850-1900, emerged before 1981 in several tropical areas in the North of Brazil, Center-West Africa and South-East Asia while it emerged after 1997 in Northern Europe and the U.S. (see page 133 of IPCC 2021). Climate models also predict heterogeneous changes in precipitation. In the high latitudes of both the Southern and Northern Hemispheres, increases in precipitation are expected as the planet continues to warm. The same holds true for the projected precipitation increases over the tropics and large parts of the monsoon regions. However, general drying is expected over the subtropical regions, particularly over the Mediterranean, southern Africa and parts of Australia and South America, including Brazil (see page 644 of IPCC 2021).

Brazil's climate has already started experiencing several of the effects of global warming discussed above. Figure I reports data from the Climatic Research Unit (CRU) at the University of East Anglia, which shows that the average temperature in Brazil has been steadily increasing since 1920, from 22.5 to 24°C. This trend shows an acceleration in the 1980s when the signal of climate change emerged in all regions of the country: temperature changes became larger than two standard deviations in the baseline period (1850-1900).[6] At the same time, an increase in the frequency and duration of droughts has been documented in Brazil, especially in the 2011-2017 period (Cunha et al., 2019). Many factors contribute to any individual extreme weather event making it challenging to attribute any particular extreme event to human-caused climate change. Still, the general trends of an increase in frequency and persistence of droughts in the Brazilian data are consistent with the predictions of climate models.

[6]For a detailed discussion, see section 1.4.2 on page 193, Figure TS.23 on page 133 and FAQ 1.3 on page 246 of IPCC (2021).

II.B Identification strategy, Weather and Climate Data

We attempt to identify factor market responses to both extreme weather events and persistent increases in dryness. The response to single extreme weather events is informative on the adjustment to climate change to the extent that the probability of each of these events is expected to increase. In turn, the response to persistent increases in dryness relative to historical averages is informative on the effects of the reduction in average precipitation in Brazil predicted by climate models. In particular, we exploit variation in drought conditions across regions and time in Brazil to identify effects of both temporary and persistent changes in dryness on local labor and capital markets.

We measure extreme weather events in Brazil using two different data sources. First, we digitized data from the National System of Civil Protection in Brazil or SINPDEC (Sistema Nacional de Proteçao e Defesa Civil). The SINPDEC data is based on reports filed by municipal authorities to the federal government when a natural disaster occurs. The objective of these reports is to provide the central government with an initial assessment of the damages and thus obtain financial and logistical support. As a result, this data allows to observe reported climatic disasters such as droughts and floods at the municipality level at a monthly frequency. Figure II displays the data for the period 2000-2018, where a marked increase in the number of reported droughts is observed after 2012. Figure III shows the geographical distribution of reported droughts across Brazil in the 2000-2010 period (a) and 2011-2018 period (b). As shown, although droughts are reported all over the country, reports tend to be clustered in the inner region of the Northeast of Brazil, as well as in the inner regions of the South and in the eastern regions of the Amazon area.

One potential concern in using SINPDEC data in our empirical analysis is that the propensity to report droughts might be correlated with other municipality characteristics that also affect our outcomes of interest. For example, poorer municipalities with less developed infrastructures to deal with exceptionally dry conditions might be more prone to reporting. In Panel A of Table I, we investigate the correlation between intensity of drought reporting in the 2000-2010 decade and initial municipality observable characteristics. We focus on this decade because the latest available Population Census of Brazil is in 2010, making this the endpoint for several of the key outcomes. As shown, municipalities reporting at least one drought between 2000 and 2010 (about half of total municipalities) have a significantly higher share of rural population, lower income per capita and alphabetization rate, and land with higher initial suitability to the main crops farmed in Brazil (soybean and maize). This is consistent with the geographical pattern documented in Figure III (a), which shows how droughts are mostly reported in inner regions of the Northeast and the South of Brazil, which tend to be more rural, more specialized in agriculture and on average poorer than coastal regions.

Thus our identification strategy relies on a climatological measure of dryness, the Standardized Precipitation and Evapotranspiration Index (SPEI), which is used by climate scientists to predict droughts (Vicente-Serrano et al., 2010). This index is computed using both precipitation and temperature levels as input data, which are produced by the CRU at the monthly level as 0.5° by 0.5° grids based on interpolated direct observations from an extensive network of weather stations. Put simply, the index compares the amount of precipitation in a given area with its potential evapotranspiration needs, which are a function of local temperature.[7] SPEI is considered superior to indices that only use information on rainfall to predict droughts caused by climate change. Dubrovsky et al. (2009) and Vicente-Serrano et al. (2010) show that the effects of warming temperatures on droughts predicted by global climate models can be clearly seen in the SPEI, whereas indices based only on precipitation data such as the Standardized Precipitation Index (SPI) do not reflect expected changes in drought conditions.

Crucially for our purposes, SPEI captures *deviations* of dryness relative to the historical average observed in a given locality during the whole 1905-2018 period.[8] A value of SPEI equal to -1 can be interpreted as the difference between observed rain and potential evapotranspiration needs being one standard deviation lower than the historical average for a given locality during that period. In the rest of the paper, we define our measure of excess dryness relative to historical averages as $Dryness = SPEI \times -1$, so that an increase in the index captures an increase in excess dryness.

In Panel B of Table I, we report the correlation between average excess dryness computed using SPEI during the 2000-2010 period in a given municipality and the same set of municipality characteristics studied in Panel A of the same Table. Because dryness is computed in deviation from average metereological conditions experienced in a given region over the very long run, we expect such "shocks" in historical climate patterns to be less correlated with socio-economic characteristics of different areas of Brazil. Indeed, we find that municipalities above and below the median of excess dryness are similar along all the important dimensions studied in this table. Still, in the empirical analysis, we control for the initial municipality characteristics reported in Table I in all specifications.

Despite the potential reporting bias, we think of data on droughts as a useful benchmark to evaluate if SPEI indeed captures dryness conditions considered so extreme by

[7]Potential evapotranspiration (PET) is defined as the evaporation from an extended surface of a short green crop which fully shades the ground, exerts little or negligible resistance to the flow of water, and is always well supplied with water. Note that this land use is assumed when computing the index regardless of actual land use.

[8]The availability of historical data is another advantage of using SPEI relative to reported droughts in our empirical analysis. Our dataset on drought reporting starts in 2000, and thus it does not permit to compare intensity in reported droughts in the last two decades with historical averages in each locality. On the other hand, meteorological variables used to compute SPEI are available starting from 1905. Because we are interested in studying the impact of a changing climate on factor reallocation, higher drought reporting in a given region might just capture more arid baseline conditions instead of an actual change in the underlying weather pattern.

local authorities to require federal assistance. To investigate if reported droughts coincide in terms of timing with dryness measured by SPEI, we perform an event-study analysis by regressing *Dryness* on twelve leads and twelve lags of reported droughts using a monthly panel at the municipality level. More specifically, we estimate the following equation:

$$Dryness_{mt} = \alpha + \sum_{k=-12}^{12} \beta_k drought_{mt}^{k} + \varepsilon_{mt}, \tag{1}$$

where m indexes municipalities, t indexes calendar months, and k indexes months relative to a reported drought in the SINPDEC data.[9] The variable $drought_{mt}^{k}$ is a dummy equal to 1 if municipality m is k months away from a reported drought, which we set at $k = 0$. For this analysis, we focus on the period between the 12 months prior and the 12 months after a drought is reported.

Figure IV plots the coefficients β_k. As shown, the deviation of *Dryness* from its mean is the highest in the month a drought is reported, around 0.7 standard deviations above the long run average dryness of that location. The figure also shows that dry weather is registered well ahead of the month a drought is reported, starting to be significantly above the long-run average around four months earlier. This suggests that the incidence of dry weather over several months is what usually triggers a report. Furthermore, the *Dryness* continues to be high during several months after the report, still being around 0.4 above the long-run average six months after a drought event is reported.

We also estimate the effect of excess dryness on the number of reported droughts per year by estimating the following panel specification at municipality-year level:

$$drought_{mt} = \alpha_m + \alpha_t + \alpha_{rt} + \beta Dryness_{mt} + \Lambda X_m \times t + \varepsilon_{mt}, \tag{2}$$

where the outcome variable is the number of reported droughts in the SINPDEC data in a given municipality and year and the main explanatory variable is excess *Dryness*. All specifications include macro-region (r) fixed effects interacted with year fixed effects, as well as the initial municipality controls used in Table I (X_{mt}) interacted with year fixed effects.[10] We report coefficient estimates for this specification separately for the first and second decade of the 2000s in columns (1) and (2) of Table II. Next, we report pooled estimates for the 2000-2018 period for which we observe both droughts and *Dryness* in column (3). As shown, higher dryness relative to historical averages strongly predicts a higher probability that a municipality reports more droughts to the federal government. The magnitude of the estimated coefficient in column (3) indicates that a municipality

[9] Since borders of municipalities changed over time, in this paper we use AMCs (minimum comparable areas) as our unit of observation. AMCs are defined by the Brazilian Statistical Institute as the smallest areas that are comparable over time. In what follows, we use the term municipalities to refer to AMCs.

[10] Brazil is divided into five macro-regions defined by the National Institute of Geography and Statistics: North, Northeast, Central-West, South and Southeast.

moving from the median to the 90th percentile of *Dryness* experienced 8 percent more droughts per year in the 2000 to 2018 period.

In Figure III (c) and (d) we report the geographical distribution of *Dryness* across Brazil in the 2000-2010 decade and the 2011-2018 decade, respectively. As shown, *Dryness* tends to be less geographically clustered in certain areas of the country relative to reported droughts. Still, the map shows how excess dryness also tends to be spatially correlated across municipalities. We take several steps in the empirical analysis to account for spatial correlation. First, whenever we investigate the indirect effect of dryness on connected regions, we exclude from our measures of exposure areas that are within a 55km radius from a given municipality. This is because the SPEI dataset is a grid with spatial resolution of 0.5° (55km $\times$ 55km). Thus, this exclusion insures that our measures of indirect exposure do not capture the effect of dryness recorded in other municipalities located within the same SPEI grid cell. We also present results with an alternative measure of exposure excluding areas within a 111km radius (1°). In addition, to account for spatial correlation in the error term, we cluster standard errors at the microregion level in all specifications. Microregions are groups of adjacent municipalities with similar production and geographic characteristics proposed by the IBGE. Brazil is divided into 558 microregions, each composed of about 8 municipalities. We report the borders of microregions in Figure III (c) and (d). In Appendix Tables A3, A4 and A5, we show that all our main results are robust to clustering at the more aggregate mesoregion level (115 regions).

Finally, we document how the distribution of excess dryness relative to historical averages across municipalities has evolved in the last two decades. Figure V (a) and (b) reports the distribution of *Dryness* (SPEI$\times -1$) across Brazilian municipalities in the first and second decade of the 2000s. As shown, while the distribution of dryness in the decade 2000-2010 is centered around the long-run average of dryness, the distribution of dryness in 2010-2020 appears to be drawn from a warmer distribution. This is consistent with the trend reported in Figure II, which shows an increase in the frequency and intensity of droughts across Brazilian regions during the last ten years relative to the previous decade.

III Empirical Analysis

In this section, we present the main results on the effects of excess dryness on the local economy of the affected regions and on the economy of regions integrated with the affected regions via capital and labor markets. We start in section III.A by analyzing the effect of excess dryness on local agricultural output. Next, in sections III.B and III.C, we study how excess dryness affects capital flows and labor flows across regions and sectors. Finally, in section III.D we propose a firm-level measure of exposure to climate-induced migration from different regions, and study its effects using social security data.

III.A Agricultural Production

III.A.1 Specification

Agricultural outcomes are observed at yearly frequency, which allows us to study both the contemporaneous effect of excess dryness and the long run effects of multiple consecutive years of unusually dry meteorological conditions.

We begin by estimating the effects of dryness on agricultural outcomes at the yearly level with the following specification:

$$y_{mt} = \alpha_m + \alpha_t + \alpha_{rt} + \beta_1 Dryness_{mt} + \Lambda Controls_m \times t + u_{mt}, \tag{3}$$

where m indexes municipalities, r indexes one of the five macro-region of Brazil, and t indexes years. Depending on the specification, *Dryness* is either the number of droughts reported in SINPDEC or SPEI$\times(-1)$. Standard errors in all specifications are clustered at the microregion level to account for spatial correlation across municipalities. All specifications include the same set of controls described in Table I interacted with year fixed effects.

To study the impact of dryness on agricultural production, we consider the following outcome variables: area planted, area harvested, and value of agricultural production (all in logs). The outcome variables are sourced from the Agricultural Production Survey (PAM), which is carried out by the Brazilian Statistical Institute (IBGE) at yearly frequency to monitor agricultural productivity at municipality level. The survey covers the 31 major temporary crops and the 33 major permanent crops farmed in Brazil. We compute the three outcomes of interest as the total area planted, total area harvested and value of production across all temporary and permanent crops surveyed in PAM. We estimate equation (3) on the time period 2000-2018.

III.A.2 Results

We start in Panel A of Table III by presenting the correlation between number of reported droughts in a given municipality and year and agricultural outcomes. The estimates of the coefficient β_1 in equation (3) show significant negative effects of droughts on area planted and area harvested. An additional reported drought is associated with a 2.6 percent decline in areas planted and a 5.3 percent decline in area harvested. Column (3) shows that the value of the agricultural production in a drought year falls by 10.7 percent, twice as much as the decline in area harvested.

In Panel B, we estimate equation (3) using SPEI$\times(-1)$ as a measure of dryness. All reported coefficients capture the effect for a municipality moving from the median to the 90th percentile of *Dryness*. We find that a municipality moving from the median to the 90th percentile of excess dryness relative to historical averages in a given year experiences a 6.4 percent decline in area planted, a 7.5 percent decline in area harvested and a 6 percent decline in the value of agricultural production. Overall, these estimates indicate that excess dryness relative to usual meteorological conditions causes sizable output losses in the agricultural sector.

We also document that the reduction in agricultural output due to excess dryness is non-linear in the level of excess dryness. Figure VI shows that municipalities in the top decile of the distribution of excess dryness suffer a loss of 16 percent in the value of agricultural production relative to those in the middle of the distribution, while municipalities in the bottom decile experience no significant change. We find similar non-linear effects of dryness also on area planted and area harvested, as shown in Appendix Figure A1. The asymmetry of these findings possibly reflects the fact that Brazilian agriculture is relatively modern and makes intense use of irrigation. Thus, experiencing a relatively wet year or a mildly dry year with respect to a normal year does not have a significant impact on overall agricultural production. High abnormal dryness, instead, is more likely to affect the water sources of the existing irrigation infrastructure, and thus have a significant effect on agricultural production.

Finally, in panel C of Table III, we study the long-run effects of experiencing almost two decades of excess dryness relative to historical averages. The outcome variable in this specification is the change in agricultural outcomes observed in a given municipality between 2000 and 2018, while the explanatory variable is the average excess dryness experienced between 2001 and 2018. We find that a prolonged period of excess dryness has large and significant effects on agricultural production. A municipality moving from the median to the 90th percentile of excess dryness relative to its historical average experienced declines in area planted and area harvested of 14.2% and 17.1% respectively, and a decline in total value of agricultural production of 22.5% in the last two decades. Overall, the substantial long-run decline in agricultural production in regions more affected by an increase in dryness relative to their historical climate conditions suggests a limited scope for local adaptation responses to climate change in the agricultural sector in our setting.

III.B Capital Reallocation

III.B.1 Specification

In this section, we study the impact of excess dryness on capital reallocation. For this analysis, we use data on bank deposits, loans and assets from the Central Bank of Brazil's ESTBAN dataset, which reports balance sheet information at branch level for all commercial banks operating in the country at the yearly level. We focus on both the direct effect of excess dryness on capital flows to and from the affected regions, and the indirect effect of excess dryness on capital flows to and from regions that are integrated with affected regions via the bank branch network. Our analysis can be summarized by the following panel specification:

$$y_{mt} = \alpha_m + \alpha_t + \alpha_{rt} + \beta_1 \underbrace{Dryness_{mt}}_{\text{Direct effect}} + \beta_2 \underbrace{ExposureDryness^K_{mt}}_{\text{Indirect effect}} + \Lambda X_m \times t + u_{mt} \tag{4}$$

where m indexes municipalities, r indexes one of the five macro-region of Brazil, t indexes years and $Dryness$ is defined as SPEI$\times(-1)$. To capture the indirect effects of excess dryness on regions connected via bank branch networks, we construct a measure of municipality-level exposure to dryness based on Bustos et al. (2020). This measure is constructed in two steps. First, we define the degree of exposure of each bank to excess dryness based on the geographical structure of its initial bank branch network as follows:

$$BankExposure_{bt} = \sum_{o \in O_b} \omega_{bo} Dryness_{ot}.$$

The weights ω_{bo} are the share of national deposits of bank b coming from origin municipality o in the baseline year 2000, O_b is the set of origin municipalities in which bank b was present in 2000. Next, we define the municipality-level exposure to excess dryness via bank branch networks as follows:

$$ExposureDryness^K_{mt} \quad = \quad \sum_{b \in B_m} w_{bm} BankExposure_{bt},$$

where the weights w_{bd} capture the lending market share of bank b in destination municipality d and are constructed as the value of loans issued by branches of bank b in municipality d divided by the total value of loans issued by branches of all banks operating in municipality d (whose set we indicate with B_d) in the baseline year 2000. The weighting should capture the total exposure of destination municipality d to any shock to funds in origin municipalities connected through bank networks.

III.B.2 Results

We start by documenting the contemporaneous effects of excess dryness on three main outcomes: loans, deposits and net capital flows. Net capital flows are constructed as the difference between loans originated by local bank branches and deposits in those same branches, normalized by assets. Thus, a positive change in net capital flows indicates that local bank branches experience an increase in lending that is larger than the increase in local deposits, implying that the municipality is a net importer of capital via the bank branch network. On the other hand, a negative change in net capital flows indicates that the municipality is exporting capital to other regions, financing loans originated by other branches of the same bank.

The main results for the year-to-year effect of excess dryness on capital outcomes are summarized in Figure VII (a) and (b), and reported in detail in Table IV. The key result reported in Figure VII is that, in the short-run, regions experiencing abnormally dry conditions experience an increase in loans originated by local bank branches. In particular, the magnitude of the coefficient in column (1) of Table IV implies that a municipality moving from the median to the 90th percentile of excess dryness experiences a 3.5 percentage points larger increase in loans. When splitting lending into agricultural vs non-agricultural loans, we find that the increase is entirely driven by agricultural loans. This is consistent with excess dryness generating a shock to the demand for funds in affected areas and predominantly in the agricultural sector.

The estimated coefficients on the indirect effects indicate that – consistent with risk sharing – regions connected via the bank network provide the necessary funds for the increase in lending in affected regions. Connected regions that provide capital to directly affected regions experience a relative decline in overall lending, concentrated in agricultural loans.[11] As shown, we find no significant direct or indirect effects on local deposits. This suggests that the direct effects on loans are not being driven by underlying trends in the local availability of capital through deposits. Instead, the results are consistent with the idea that regions experiencing abnormally dry conditions insure themselves in the short run against negative shocks by importing capital via the banking sector, while connected regions provide that insurance and are net exporters of capital. The magnitude of the estimated coefficient on the direct effect of excess dryness on net capital flows indicates that a municipality moving from the median to the 90th percentile of excess dryness experiences a 1.5 percentage points larger net inflow of capital as a share of assets of local bank branches (column (5) of Table IV). On the other hand, a municipality moving from the median to the 90th percentile of exposure to dryness via banks experiences a 1.1 percentage points larger net outflow of capital.

Next, we study the long-run effects of direct and indirect exposure to excess dryness. We estimate a version of equation (4) where the outcome variables are long-run changes in loans, deposits, and net capital flows at municipality level between 2000 and 2010. We focus on the 2000 to 2010 decade to match the analysis on labor reallocation using the Population Census years presented in section III.C.

The results are summarized in Figure VII (c) and (d) and reported in detail in Table V. The key results reported in Figure VII show that, in the long run, excess dryness generates lower lending in both directly affected and indirectly affected regions. The magnitude of the estimated coefficient in column (1) of Table V indicates that a municipality moving

[11] A potential explanation for this latter result is that Brazilian financial institutions are required to allocate 25% of unremunerated deposits (i.e. deposits in checking accounts) to agricultural loans. This constraint is binding for most banks, which would rather allocate less than the target threshold to the agricultural sector. When such banks experience an increase in lending demand in affected areas, they might compensate by decreasing their loan origination in non-affected areas so to keep their overall exposure to the agricultural sector at the mandated minimum.

from the median to the 90th percentile of average excess dryness over the 2001 to 2010 period experienced a 11.8 percent decline in the balance of outstanding loans originated by local branches. Importantly, in the long run, the relative decline in loans occurs also outside of the agricultural sector. In fact, the magnitude of the estimated coefficient indicates that the decline is twice as large for non-agricultural loans than for agricultural loans. The decline in lending following a full decade of abnormally dry climate is consistent with a general decline in local economic opportunities and thus current and expected future income for firms and individuals in directly affected areas. This, in turn, depresses the demand for external finance as in a standard permanent income framework. The decline in lending is also consistent with lower approval rates of loan applications by local bank branches if multiple years of abnormally dry climate lead to lower repayment (de Roux, 2021).

Differently than in the short-run results, when we study indirect effects over a full decade, we find that also regions more exposed to excess dryness via banks experience a significant decline in total lending. In other words, in the long run, connected regions stop providing insurance. The magnitude of the effect is about half the size of the direct effect, but precisely estimated and with similar magnitudes for agricultural and non-agricultural lending. A potential mechanism for this result is that connected municipalities are negatively affected by abnormally dry climate at origin due to an increase in non-performing loans in directly affected municipalities served by the same banks.[12] More defaults imply lower liquidity available at the bank level to originate loans across all branches.

Similarly to the short-run results, most of the adjustment by the banking sector is concentrated in lending activity, while deposits tend to be stickier. We find negative but mostly non statistically significant effects of excess dryness on changes in total deposits at the decadal level. The combination of the effects on lending and deposits implies that, in the long run, excess dryness generates larger capital outflows in both directly and indirectly affected regions. The magnitude of the estimated coefficients in column (5) of Table V indicates that a municipality moving from the median to the 90th percentile of average excess dryness over the 2001 to 2010 period experiences a 3.9 percentage points larger outflow of capital. Similarly, indirectly affected municipalities experience a larger net outflow of capital of about one third of the magnitude of the direct effects, although this estimate is less precisely estimated.

Overall, the results presented in this section provide new insights on the role of the banking sector in capital reallocation due to climate change. Our findings indicate that, in the short run, the local financial system favors risk sharing in areas affected by climate shocks with the support of connected areas. However, over the long run, the evidence

[12]See on this also evidence from Aguilar-Gomez et al. (2022), which documents that increases in extremely hot days predict higher loan defaults by local firms using data from Mexico.

indicates that the financial system reduces credit allocation towards areas affected by abnormal climate. In the long run, the evidence also indicates that higher exposure to regions more affected by climate change might affect aggregate lending activity at the bank-level.

III.C Labor Reallocation

III.C.1 Specification

We now turn to Population Census data to analyze the impact of excess dryness on labor reallocation in the 2000 to 2010 decade. As in section III.B, we aim to capture two types of effects. First, due to the local impact of exceptionally dry weather on agricultural productivity, which potentially also affects other sectors through general equilibrium effects, excess dryness directly affects local labor markets. We estimate this direct effect by using the average excess dryness between 2001 and 2010 as regressor. Second, when a spatial reallocation of factors occurs, regions that are not directly affected by dryness but destinations or origins of factors that move might also experience changes in their labor markets.

To capture this indirect effect of dryness on labor flows, we construct a measure of municipality-level exposure to excess dryness via migration links. For this, we assume that destinations that in the past received a higher share of migrants from certain origins are more likely to receive migrants from these origins when excess dryness occur there. Thus, we employ the well-documented network channel, according to which migrants tend to choose destinations that were previously chosen by migrants from their same origin region (Altonji and Card, 1991; Card, 2001). The Brazilian Census allows us to construct internal migration flows based on a question asking respondents for their municipality of residence five years prior to the Census year. Thus, using the 2000 Census, we calculate bilateral migration flows between each pair of municipalities during the period 1995-2000.[13] We then construct the exposure to dryness via migration links as

$$ExposureDryness^{L}_{m,2001-2010} = \sum_{o \neq m} \alpha_{om} Dryness_{o,2001-2010},$$

with

$$\alpha_{om} = \frac{M_{1995-2000,o\to m}}{M_{m,2000}},$$

where o denotes the origin municipality, m the destination municipality, $M_{1995-2000,o\to m}$ the size of the migrant flow from o to m between 1995 and 2000, and $M_{m,2000}$ the total number of individuals that migrated during this period to m.

[13]Note that since the Census question refers to the place of residence five years ago but not the previous place of residence, these migration flows also include those individuals that moved more than once during the last five years and therefore potentially not directly from origin to destination.

Having created the measures for direct effects and indirect effects, we estimate the following specification:

$$\Delta y_{m,2000-2010} = \beta_1 \underbrace{Dryness_{m,2001-2010}}_{\text{Direct effect}} + \beta_2 \underbrace{ExposureDryness^{L}_{m,2001-2010}}_{\text{Indirect effect}} + \alpha_r + \gamma X_m + \varepsilon_m, \tag{5}$$

where X_m is the same set of controls for municipality characteristics described in Table I.

Note that exposure via the migrant network described above and via the bank branch network described in section III.B are not the only possible connections between municipalities. One obvious additional network linking municipalities is trade in goods. Because we do not have access to detailed data on bilateral trade flows across municipalities in Brazil, we construct a measure of exposure to dryness via trade links using the road network as follows:

$$ExposureDryness^{T}_{m,2001-2010} = \sum_{o \neq m} \tau_{om}^{-\theta} Dryness_{o,2001-2010},$$

where τ_{om} is the trade cost between municipalities o and m and θ is the trade elasticity. This functional form follows the formula for market access proposed by Donaldson and Hornbeck (2016) in their empirical estimation, replacing population with our measure of decadal $Dryness$. The trade cost is based on the bilateral traveling cost via the highway network in the year 2000. Following Astorga (2019), we obtain the traveling costs c_{om} by dividing Brazil in grid cells and applying the fast marching method algorithm to determine the most efficient route between each pair of municipalities under the assumption that crossing a cell without a federal highway has a traveling cost 3.5 times higher than one with a federal highway. As in Allen and Arkolakis (2014), we then compute trade cost as the exponential form $\tau_{om} = \exp(c_{om})$. For the trade elasticity θ, we use the estimate of 3.39 by Astorga (2019).

For readability, in the next section we only report the coefficients on exposure to dryness via the migrant network and the bank branch network. This is because exposure to excess dryness via trade links has mostly small and non significant effects on our main outcomes, as can be seen in Appendix Table A2. However, exposure via trade links is included as a control in all specifications presented below.

III.C.2 Results

Migration.

We start by studying the direct and indirect effects of excess dryness on net migration flows between 2005 and 2010. We compute net migrant flows as the difference between overall inflows and outflows of individuals, which are the sums of the 2005-2010 bilateral migration flows, relative to 2010 population:

$$netflows_{m,2005-2010} = \frac{inflows_{m,2005-2010} - outflows_{m,2005-2010}}{population_{m,2010}}$$

Notice that we compute these flows between 2005 and 2010 because the 2010 Census asks all respondents for their municipality of residence five years prior to the Census year. An increase in *netflows* corresponds to an increase in net migration *into* a given municipality, while a decline in this variable corresponds to an increase in net migration *out* of a given municipality.

The key findings are summarized in Figure VIII and reported in detail in Table VI. The main finding documented in Figure VIII is that excess dryness generates net outflows of migrants from directly affected municipalities and net inflows of migrants into indirectly affected ones. More specifically, a municipality moving from the median to the 90th percentile of excess dryness experiences a 1.44 percentage points larger net outflow of migrants as a share of its population. On the other hand, a municipality moving from the median to the 90th percentile of indirect exposure to excess dryness via pre-existing migration networks experiences a 0.82 percentage points larger net inflow of migrants as a share of their population.

In the same figure, we decompose net migration flows into outflows and inflows. The negative direct effects are mainly driven by an increase in outflows of migrants from affected regions, while the positive indirect effects are mainly driven by an increase in inflows of migrants in connected regions. Overall, these results indicate that excess dryness generates a reallocation of labor from directly affected regions to regions that are connected via pre-existing migration networks.

In Table VI we also report the results of estimating a version of equation (5) including both the municipality exposure to excess dryness via migrant networks and the municipality exposure to dryness via bank branch networks. The results are reported in column (3). As shown, the results on net migration flows are very robust to the inclusion of exposure via bank networks, suggesting that the two measures of exposure capture networks with different geography. Indeed, Table A1 shows that the correlation between the measures of exposure via migrants and via banks is 0.157. The results in column (3) of Table VI also show that exposure via bank branch networks has no explaining power on net migration flows.

Finally, we present some diagnostics on the issue of spatial correlation. Figure III (c) shows that SPEI tends to be spatially correlated across regions of Brazil. As discussed in section II, when we study the indirect effect of dryness on connected regions, we exclude from our measures of exposure areas that are within a 55km radius from a given municipality. To assess the impact of spatial correlation in *Dryness* on our ability to separate direct vs indirect effects, in Figure A2 we report how our key estimates of direct and indirect effects of dryness on net migration flows change when we do not exclude areas within a 55km radius, and when we exclude larger areas around each municipality. As shown, both direct and indirect effects are very stable in terms of magnitude if we do not exclude nearby municipalities or if we exclude municipalities within a 111km radius. However, the figure also shows that estimates become less noisy when removing nearby locations from the measures of indirect exposure. This is consistent with the fact that this spatial adjustment lowers the correlation between direct and indirect measures of exposure to excess dryness, allowing us to better separate direct and indirect effects.

Employment, Wages and the Sectoral Structure of the Economy.

Next, we study the direct and indirect effects of excess dryness on the change in total employment between 2000 and 2010. Total employment is sourced from the Population Census data and covers both formal and informal labor. The results are reported in Table VII. The estimates in column (3), which include all the measures of indirect exposure, indicate that moving from the median to the 90th percentile of excess dryness implies a 2.9 percent decline in total employment over the 2000 to 2010 period. Consistent with the results on net migration flows, the indirect effect of a higher exposure to excess dryness via migrant networks is a 2.1 percent increase in employment. We also find that exposure via bank branch network has a negative and significant effect on employment of 1.3 percent. We discuss this result in more detail below when decomposing the effect on employment by sector.

Next, we study the effect of excess dryness on the sectoral structure of the economy of both directly affected and indirectly affected municipalities. The results are summarized in Figure IX and reported in columns (4)-(6) of Table VII. The outcome variables are changes in log employment in each sector between 2000 and 2010. We focus on the effects on 4 broad sectors: agriculture, manufacturing, services and a residual sector labeled “other”, which includes public sector workers, construction, extractive industry and utilities.

In line with the negative impact on agricultural productivity documented in section III.A, we find a large and negative direct effect of excess dryness on agricultural employment. Municipalities at the 90th percentile of excess dryness experience a 7.3 percent larger decline in agricultural employment than those at the median between 2000 and 2010. The service sector also experiences a significant decline in directly affected areas. This is consistent with services being mostly non-tradable, and thus negatively affected by a decline in local demand due to the negative agricultural production shock.[14] We find that local manufacturing absorbs some of the displaced workers. This is consistent with a standard small open economy model in which agriculture and manufacturing are tradable sectors and services is non-tradable. A simple back of the envelope calculation indicates that only about a third of the workers released by agriculture, services and other

[14]Note that a similar argument also applies to the "other" sector, which includes non tradable sectors such as construction and experiences a relative decline in size in directly affected areas.

sectors relocate locally into manufacturing. The remaining workers either migrate – as documented above – or remain unemployed locally. Recall that Census data includes both formal and informal labor, and therefore any reallocation across sectors that also entails a reallocation to or from informality is captured in the estimates of Table VII.

Looking at the indirect effects, we find that regions more exposed to climate migrants expand employment in all sectors with the exception of manufacturing. More specifically, relative to those at the median, municipalities at the 90th percentile of exposure to excess dryness via the migrant network experience increases of 2.9%, 2.2%, and 3.1% in agriculture, services and other sectors, respectively, while the effect for manufacturing employment is small and not statistically significant. This implies a decline in the share of manufacturing employment in regions indirectly exposed to excess dryness via migration. The results of Table VII document an asymmetry in the ability of the manufacturing sector to absorb workers in regions directly affected vs regions indirectly affected by excess dryness. We investigate this new result further in section III.D by relying on firm-level data.

Table VII also shows that the negative indirect effect of exposure to excess dryness via the bank network on employment is concentrated in the manufacturing sector, as can be seen in column (5). Recall from section III.B that regions connected via the bank branch network experience a decline in overall lending during the 2000-2010 decade, possibly due to a negative liquidity shock from an increase in non-performing loans in agriculture. Table VII documents that this negative indirect effect on bank liquidity negatively affects the manufacturing sector, which is traditionally characterized by a higher capital intensity than the rest of the economy.

Finally, we study the direct and indirect effects of excess dryness on total population and average wages. The results are reported in Table VIII. Two main findings emerge from this table. First, consistent with the documented effects on net migration flows, regions directly affected by excess dryness experience a relative decline in population, while regions indirectly affected via the migrant network experience a relative increase in population. Column (2) shows that the positive indirect effect of exposure to excess dryness via the migrant network is partially mitigated by the negative indirect effect of exposure via the bank branch network, which is consistent with our findings on lending and employment discussed above. Second, we find small and non statistically significant direct effects of excess dryness on changes in average wages between 2000 and 2010. A potential explanation is that the negative agricultural productivity shock caused by excess dryness – which we would expect to negatively affect wages – is accompanied by a change in the composition of the local labor force, whereby the former agricultural and services workers migrating out of affected regions were those earnings relatively lower wages at baseline. The indirect effects on changes in average wages are also small and not statistically significant.

Overall, the results presented in this section indicate that a full decade of abnormal dryness affects the structure of both the local economy and the economy of areas connected via migrant networks.

III.D Labor Reallocation at Firm-level

III.D.1 Specification

In this section, we bring the analysis of labor reallocation across regions and sectors to the firm-level. This analysis has two objectives. First, to explore in more detail the lack of reallocation of workers into manufacturing in destination municipalities. In section III.C, we documented that excess dryness generates a decline in employment in directly affected regions which is, however, partly absorbed by local manufacturing, plausibly because it is a tradable sector whose demand is less affected by local shocks. On the other hand, we also documented that regions that receive climate migrants do not experience an increase in manufacturing employment. Thus, in this section, we use detailed data that allows us to track workers' movements across regions and sectors to shed light on this result. The second objective of this analysis is that it allows us to make progress on the identification front by exploiting variation across firms within the same destination municipality. In particular, we exploit variation across firms that are differently exposed to migration flows from regions experiencing excess dryness, but that are located within the same municipality. Comparing firms within the same municipality allows us to fully control for other aggregate effects at municipality level that are common across firms.

We measure workers' flows using social security data from the Annual Social Information System (RAIS). RAIS is an employer-employee dataset that provides individual information on all formal workers employed in Brazil, including the municipality in which they work and the sector of their employer.[15] Workers have unique identifiers that allow us to follow them over time.

We propose a new firm-level measure of exposure to past migration from different origins within Brazil. Our approach is akin to the one used to compute the measure of municipality exposure described in section III.C. As a first step, we construct weights capturing the degree of labor market integration between each municipality in Brazil and a given firm. To compute these weights, we use past migration flows as follows:

$$\alpha_{oi(m),t^*} = \frac{L_{i(m),t^*,o\rightarrow d}}{L_{i(m),t^*}} \tag{6}$$

[15]Employers are required by law to provide detailed worker information to the Ministry of Labor. See Decree n. 76.900, December 23^{rd} 1975. Failure to report can result in fines. RAIS is used by the Brazilian Ministry of Labor to identify workers entitled to unemployment benefits (*Seguro Desemprego*) and federal wage supplement program (*Abono Salarial*). For the analysis in this paper we restrict to firms with at least 5 employees. Following previous literature, we focus on workers employed at the end of year and, for workers with multiple jobs, focus on the one with the highest salary, so that each individual appears only one in each year (Bustos et al., 2020; Dix-Carneiro and Kovak, 2017; Helpman et al., 2017).

Where $\alpha_{oi(m),t^*}$ is the share of workers employed in the baseline year t^* in firm i whose last observable move was from origin municipality o to the destination municipality m, the one where the employer i is located in year t^*. When mapping equation (6) to the data, we construct past workers' movements using the period 1998 to 2005, and define our baseline year $t^* = 2005$.

Next, we use these weights to predict future worker flows between origin municipality o and destination firm $i(m)$. The rationale is similar to the municipality-level regressions presented in section III.C. At the firm level, it implies that migrant workers moving from a given origin o tend to follow employment trajectories similar to those of previous migrants from their same origin region. This could be, for example, because firms at destination hire new workers using referrals from current employees, and current employees are more likely to know or vouch for individuals from their same region.

We estimate the following specification at the firm-origin level:

$$\underbrace{\frac{L_{oi(m),2006-2010}}{L_{i(m)}}}_{\substack{\text{worker flow}\\ \text{from origin } o\\ \text{to firm } i}} = \alpha_m + \beta_1 \alpha_{oi(m)} + \beta_2 \underbrace{\alpha_{oi(m)}}_{\substack{\text{firm initial}\\ \text{exposure to } o}} \times \underbrace{1(Dry)_o}_{\substack{=1 \text{ if } o\\ \text{top quartile}\\ \text{of } Dryness}} + \beta_3 1(Dry)_o + \varepsilon_{oi(m)}$$

The outcome variable in equation (7) is the flow of migrants to firm i from a given origin o. More precisely, it is the number of migrant workers that moved from origin municipality o to firm $i(m)$ (where $o \neq m$) between 2006 and 2010, normalized by the total number of workers of firm $i(m)$ observed on average in the same period. This flow can be regressed on a measure of the baseline exposure of firm $i(m)$ to migrants from a given region, and an interaction of such exposure with excess dryness that occurred in the origin between 2006 and 2010. To make estimation computationally less intensive, we aggregate all potential origin municipalities in two groups: origins that experienced very high excess dryness during the 2006-2010 period, which we define as those in the top quartile of $Dryness = SPEI \times -1$, and those that did not. Municipalities in the top quartile of $Dryness$ experienced, on average, 0.76 of a standard deviation higher excess dryness than those in the rest of the distribution in the same years.

Constructing a measure of exposure to migrant flows at the firm-municipality of origin level allows us to exploit variation across firms that operate in the same destination municipality, and thus control for any unobservable common shock in the destination labor market. It also allows us to saturate the model presented in equation (7) with firm fixed effects. This effectively absorbs any heterogeneity in firm-level shocks, so that the coefficient of interest β_2 captures within firm-variation in migrant workers' flows from regions that are heterogeneously affected by excess dryness.[16] In all specifications we cluster

[16]Since we aggregate origins in two groups, the dummy $1(Dry)_o$ effectively captures the origin fixed effect.

standard errors at the destination municipality level to account for spatial correlation of the error terms across firms operating in the same region.

III.D.2 Results

Before discussing our main results, we present some stylized facts on firm connections to regions exposed to climate change. In particular, we study how such composition varies across firms operating in different sectors and for firms of different size. We compute the degree of firm connections to certain regions by taking the average of the interaction between the weights capturing the share of migrant workers from each origin and a dummy capturing regions more exposed to excess dryness in the 2006-2010 period. In practice, this corresponds to computing the average of the interaction of interest in equation (7) – i.e. $\alpha_{oi(m)} \times 1(Dry)_o$ – across firms in a given sector or firms in a given size category.

Figure X (a) reports the results by sector. The first finding is that firms in agriculture tend to be more connected to regions more affected by excess dryness via their network of migrant workers. The magnitudes indicate that the average firm in agriculture has, at baseline, 6 percent of workers coming from regions that experienced high excess dryness in the 2006-2010 period, about four times more than firms in the manufacturing sector. Among the four main sectors used in our analysis, agriculture and services show the highest connection to areas affected by climate change, while manufacturing has the lowest connections. This stylized fact underlines a potential explanation for the lack of reallocation of climate migrants into manufacturing in indirectly affected regions. Namely, the fact that manufacturing firms are initially less connected to regions experiencing high excess dryness via past migrant links. If the geographical distribution of excess dryness is as good as randomly assigned across municipalities of Brazil, this suggests that manufacturing firms are in general less connected to any region via migrant networks, potentially because they are more likely to be clustered in certain regions and to source their employees locally.

In Figure X (b), we report the same statistics but splitting firms by size.[17] Differences in the intensity of connections to regions more exposed to climate change are less stark across the firm size distribution. We find that, on average, the degree of initial connection with areas experiencing high excess dryness is increasing in size, with large firms' initial connections being about 30% higher than those of small firms.

Table IX reports the results of estimating equation (7). The objective of this analysis is to study whether excess dryness in origin regions explains workers' flows to destination firms. To this end, we compare firms in the same destination municipality, and study whether those initially more connected to regions more affected by climate change also experience larger inflows of workers from those regions. In column (1), we estimate a

[17]We define as micro firms those with less than 10 employee, as medium firms those with between 10 and 49 employees, and as large firms those with at least 50 employees.

version of equation (7) with origin fixed effects, destination municipality fixed effects and our measure of exposure to migrants from a given region as explanatory variables. The estimated coefficient β_1 indicates that, in the 2006-2010 period, firms receive larger flows of migrant workers from regions with which they were initially more connected. The magnitude of the coefficient indicates that firms with a 10 percent larger initial connection to a certain origin municipality experience a 6 percent larger flow of workers from that region. This magnitude describes the increase in flows relative to other firms operating in the same destination municipality.

In column (2), we include the interaction term between connection to a certain origin region and a dummy capturing whether the origin experienced high excess dryness. The point estimates of both β_1 and β_2 are positive and statistically significant. The estimated coefficient β_2 indicates that worker flows to destination firms are relatively larger from origin municipalities that experience a larger increase in excess dryness during the 2006-2010 period.

Even within a given destination municipality, firms more connected to areas with higher excess dryness via past migrant workers might be more connected to those areas also via trade networks or financial links. If that is the case, then the coefficient β_2 cannot be interpreted as capturing the effect of climate change on firms via labor reallocation. Thus, in column (3), we estimate equation (7) including firm fixed effects. This specification absorbs any firm-level differences in exposure to areas more affected by climate channels via other channels. We find that, when fully accounting for firm-level differences, the estimated coefficient β_2 remains positive and increases in magnitude, which indicates that other firm-level connections with areas with high excess dryness tend to have a negative effect on firm growth.

In columns (4)-(6) we split our sample by sector. As shown, the differential increase in worker flows from areas with high excess dryness is relatively similar across sectors, with larger coefficients for agriculture than manufacturing and services. As documented in Figure X, agricultural firms tend to be on average more connected to affected areas via their past workers' flows. Our estimates indicate that agricultural firms with average connection to areas with high excess dryness experience a 2.2 percent larger flow of workers from such regions.[18] This effect is about three times larger than the one observed for firms in manufacturing (0.7 percent) and services (0.8).

Next, in columns (7)-(9), we split our sample by firm size. We find that smaller firms tend to have larger elasticities of workers' flows from climate change exposed regions. In particular, firms with less than 10 employees (micro firms) with average connection to areas with high excess dryness experience a 1.3 percent larger flow of workers from such regions. This elasticity is 1.1 percent for medium-sized firms, and 0.7 percent for large

[18] We compute this effect by multiplying the estimated coefficient β_2 in column (4) of Table IX by the average connection of agricultural firms to Dry origins.

firms.

We believe that these results have two main implications. First, they are consistent with the existence of frictions driving the allocation of workers in the Brazilian labor market. They show that workers' trajectories tend to follow pre-existing connections with their place of origin, and that the impact of these pre-existing connections on flows is larger for small firms. Small firms tend to be characterized by lower skill intensity and lower average wages – characteristics that in the literature have been associated with lower productivity.[19] This implies that climate-driven worker flows might not be allocated efficiently. Second, the results indicate that labor reallocation driven by climate change can retard the structural transformation process in destination regions. Displaced workers tend to be absorbed at a higher rate in agriculture than in manufacturing. Existing research has shown that labor productivity is lower in agriculture than in the rest of the economy (Caselli 2005, Restuccia et al. 2008, Lagakos and Waugh 2013), and that the manufacturing sector is characterized by economies of scale and knowledge spillovers that can lead to higher long-run growth (Krugman 1987, Lucas 1988, Matsuyama 1992).

IV Concluding Remarks

Climate change is expected to reduce agricultural productivity in most developing countries located in tropical and subtropical areas. We study the experience of Brazil to provide direct evidence on how capital and labor adjust to changes in climate. To capture the effect of climate change we use the SPEI, a measure of excess dryness in a location defined as its moisture deficit relative to its 100-year average, which is based on local precipitation and temperature data.

Using SPEI, we document that regions with higher excess dryness experience large declines in agricultural output. In the short run, local economies insure themselves against negative weather shocks via financial integration with other regions. However, in the long run, affected regions experience large declines in agricultural production and significant capital outflows, driven by a reduction in loans, consistent with a permanent decrease in investment opportunities. We also find that abnormal dryness affects the structure of the local economy. Directly affected areas experience a sharp reduction in population and employment, concentrated in agriculture and services. While local manufacturing absorbs part of the displaced workers, these regions experience large out-migration. Overall, the combination of large long-run effects on agricultural production and outflows of labor and capital suggest limited scope for local adaptation responses.

Regions receiving climate migrants expand employment in agriculture and services, but not in manufacturing. Using social security data, we provide evidence that labor

[19] See Lucas (1978); Melitz (2003) for classic models of the firm in which more productive firms tend to be larger. Empirically, see Syverson (2004) for a discussion of the correlation between firm size and quantity based measures of total factor productivity.

market frictions direct migrants to firms connected to migrants' social networks, which are mostly disconnected from manufacturing firms at destination. This force generates de-industrialization and increases the weight of small firms in the firm size distribution in destination regions.

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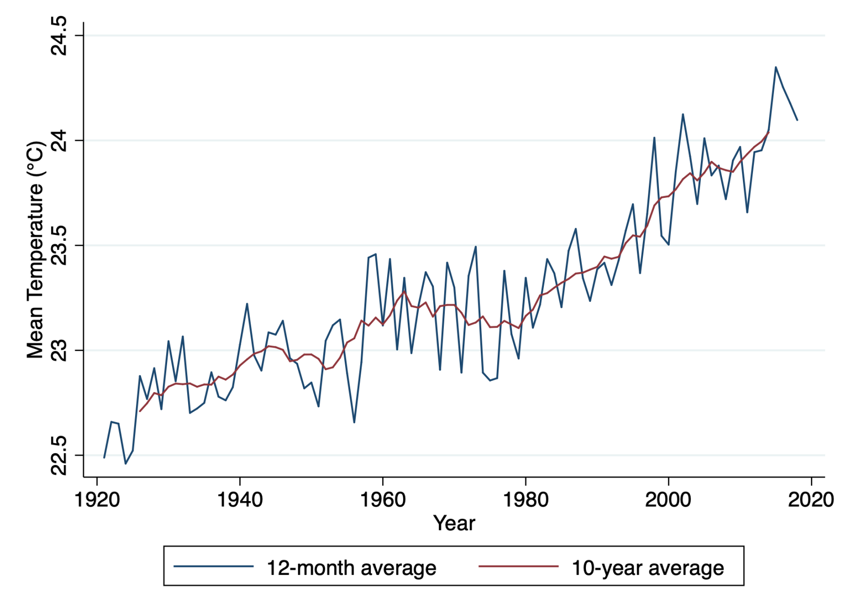
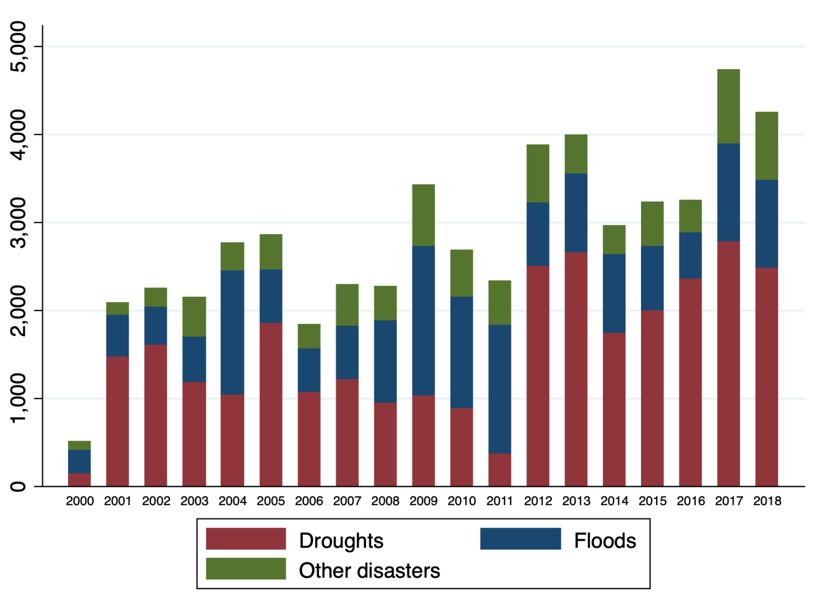
Figures

Figure I: Average temperature in Brazil since 1920



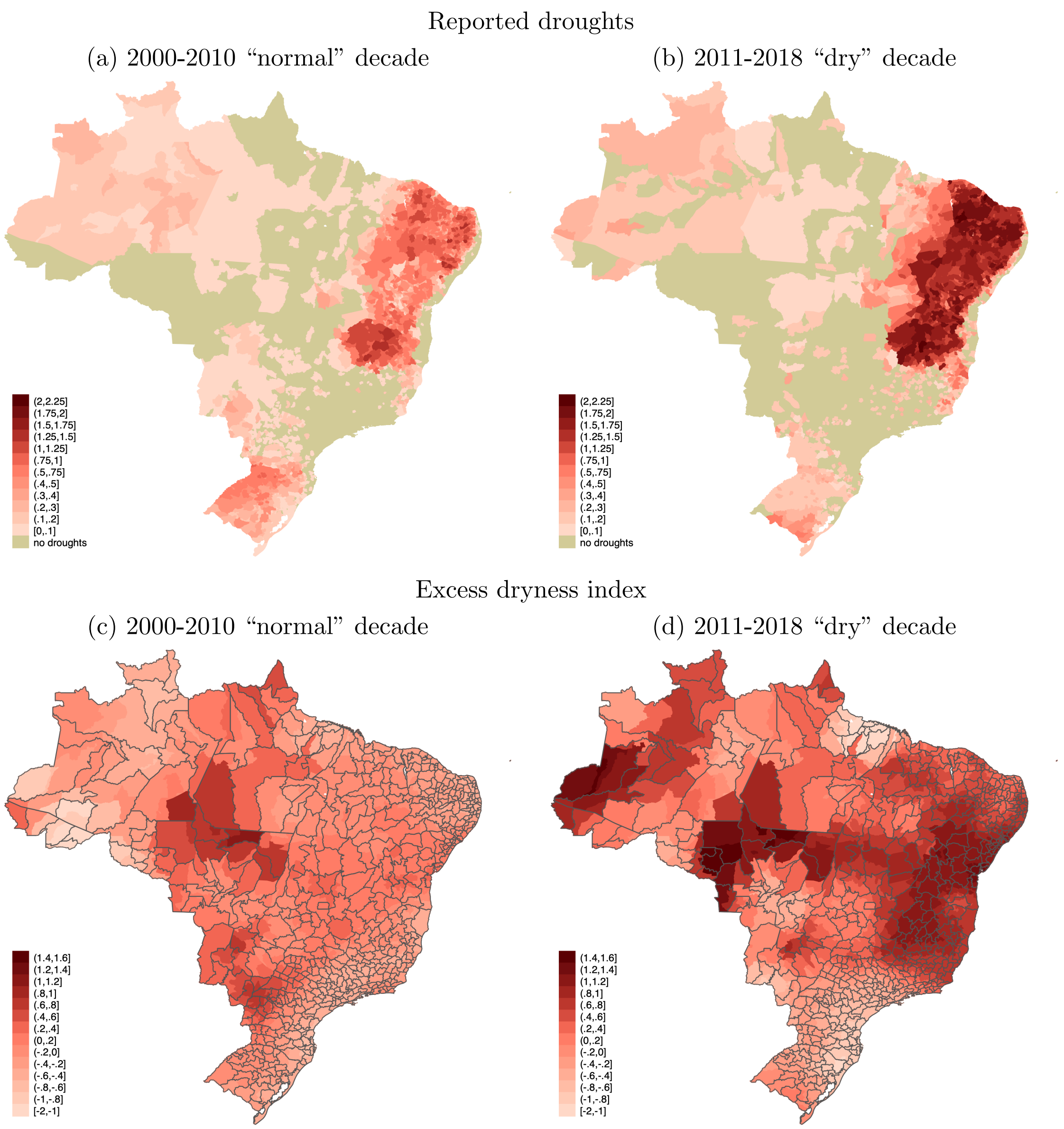
Source: Climatic Research Unit, University of East Anglia.

Figure II: Reported Natural Disasters By Year: 2000-2018



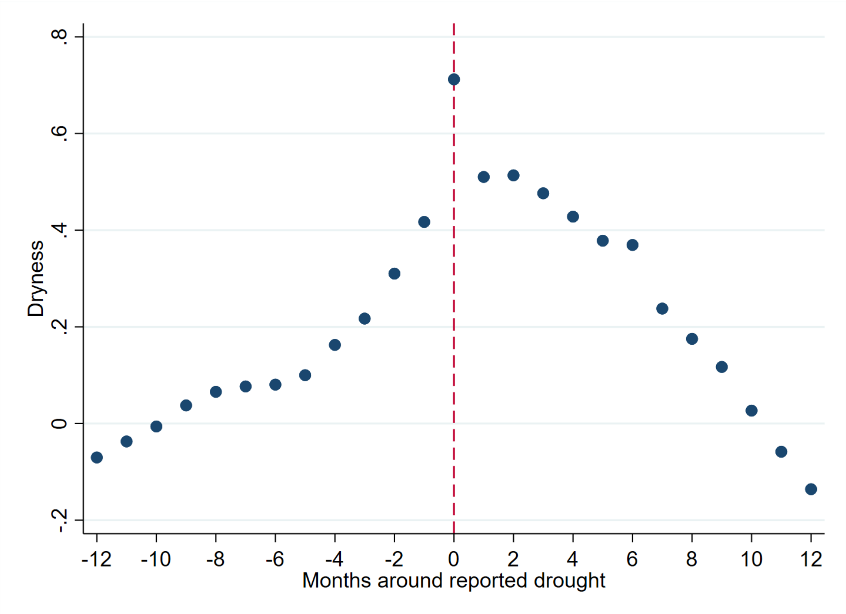
Source: Sistema Nacional de Proteçao e Defesa Civil - SINPDEC

Figure III: Geographical distribution of reported droughts and SPEI



Notes: Maps (a) and (b) show the average number of reported droughts per year during the indicated time period. Maps (c) and (d) show the excess dryness index (average SPEI multiplied by -1) during the indicated time period as well as the borders of the 558 microregions of Brazil, the level of clustering of standard errors used in the empirical analysis to account for spatial correlation in the error term.

Figure IV: Average excess dryness index around drought events

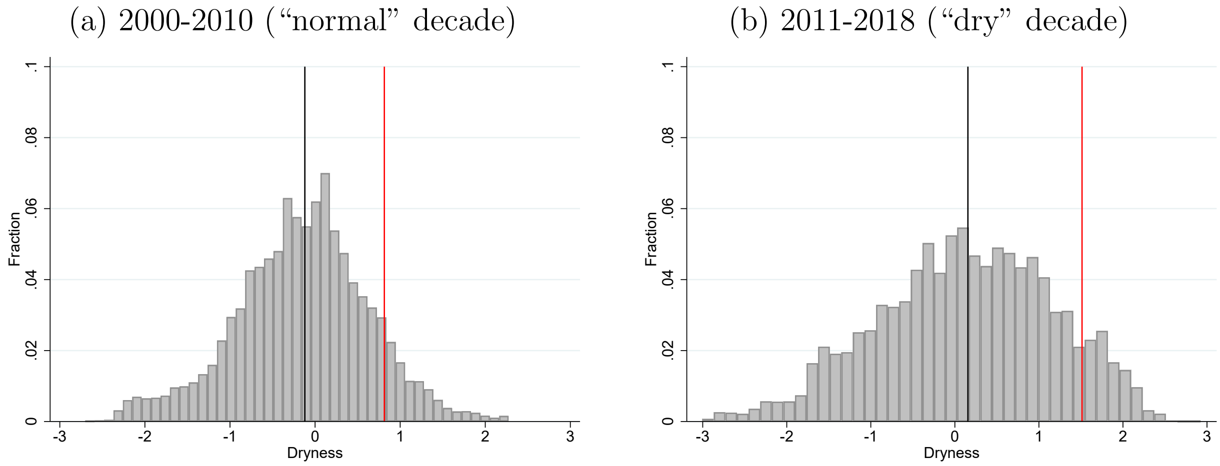


Notes: The figure shows the β_k coefficients estimated using the following equation:

$$Dryness_{mt} = \alpha + \sum_{k=-12}^{12} \beta_k drought_{mt}^{k} + \varepsilon_{mt},$$

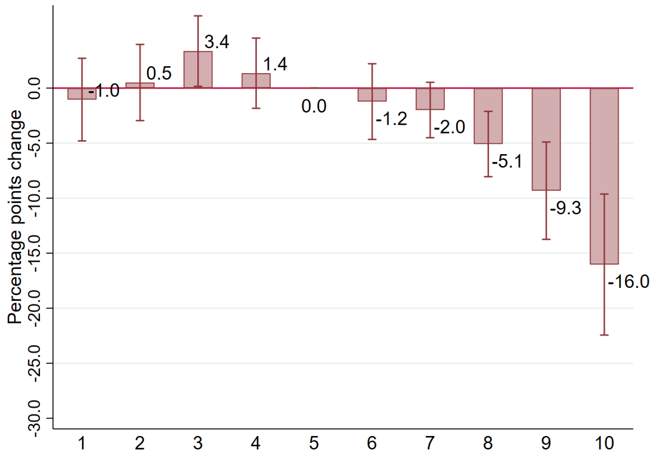
where Dryness is defined as SPEI$\times -1$, and *drought* is a dummy indicating a reported drought in municipality m and month t. We plot the coefficients on the 12 leads and 12 lags of the dummy *drought*, using monthly data at the municipality level from 2000 to 2018.

Figure V: Distribution of Excess Dryness Index Across Municipalities



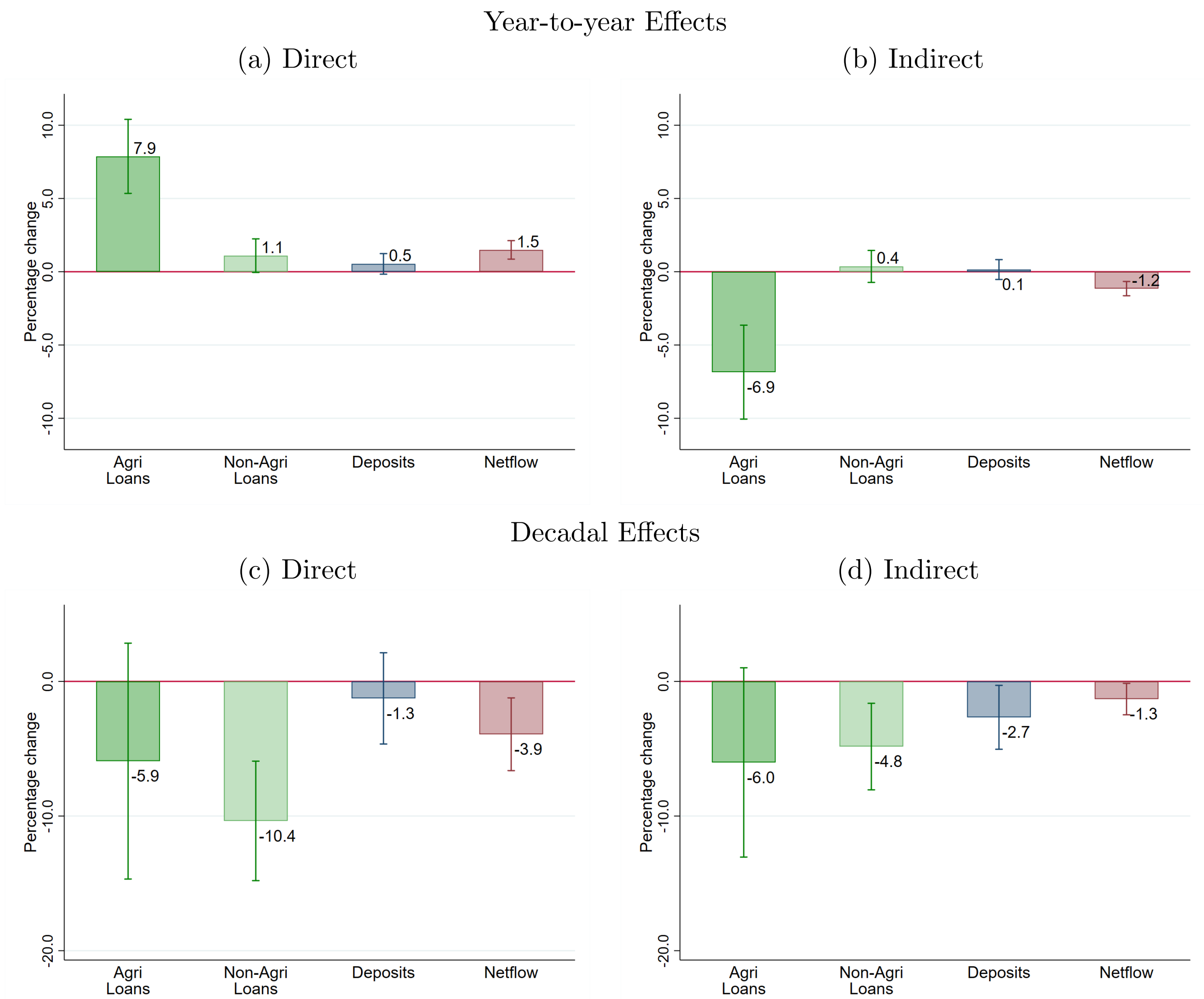
Notes: The figure shows the distribution of *Dryness* (SPEI$\times -1$) across Brazilian municipalities by decade. The black line in both graphs represents the 50^{th} percentile of the distribution, while the red line in both graphs represents the 90^{th} percentile of the distribution. Quantifications in the paper are computed for a municipality moving from the 50^{th} to the 90^{th} percentile of excess dryness. This corresponds to about 1 standard deviation of excess dryness in the 2000-2010 decade, and to 1.36 standard deviations in the 2011-2018 decade.

Figure VI: Effects of Excess Dryness on Value of Production in Agriculture By Decile of Dryness



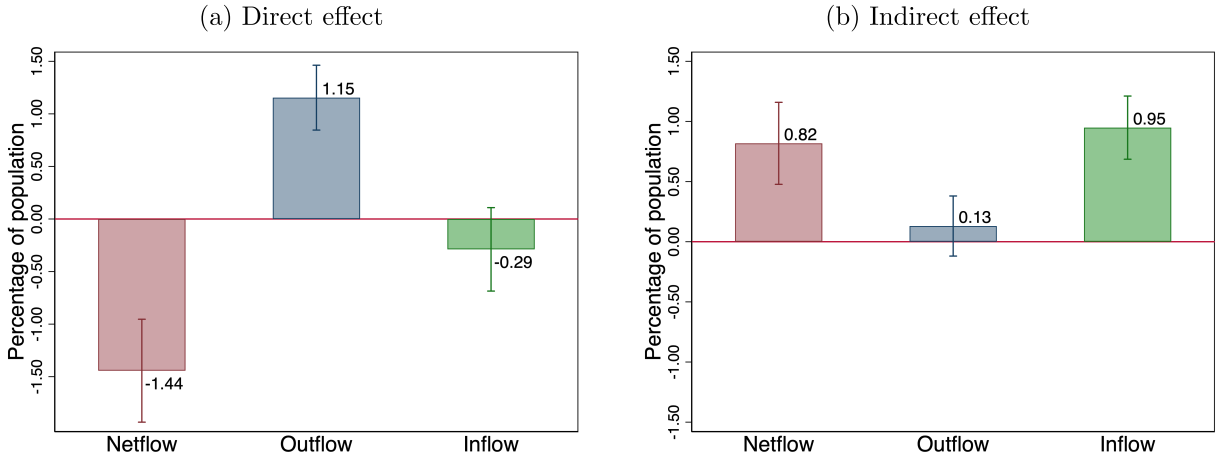
Notes: The figure shows the estimated coefficients on dummies capturing deciles of the excess dryness index in a panel regression at municipality-year level for the period 2000 to 2018 where the outcome variable is the log value of agricultural production of all crops covered by the PAM survey (temporary and permanent). Deciles of *Dryness* go from the wettest to the driest. Estimated effects are relative to the 5^{th} decile. Controls include AMC fixed effects, macro-region times year fixed effects and the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yields, each interacted with year dummies. Vertical lines are 90 percent confidence intervals.

FIGURE VII: EFFECTS OF EXCESS DRYNESS ON LOANS, DEPOSITS AND CAPITAL FLOWS: YEARLY VS DECADAL EFFECTS



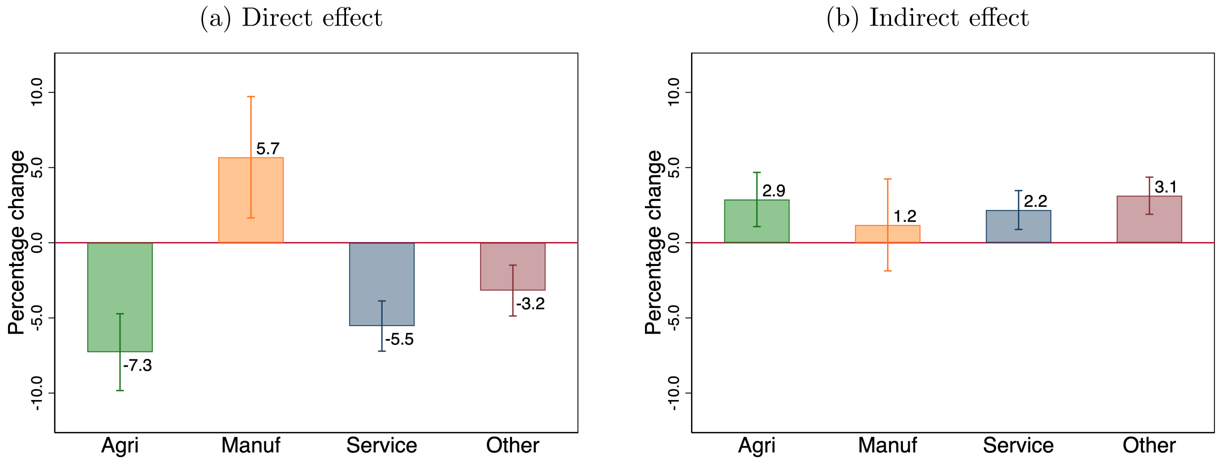
Notes: The figure reports the estimated effects (in percentage points) on capital outcomes for a municipality going from the 50th to the 90th percentile in the direct and indirect (exposure via banks) measures of excess dryness. Panels (a) and (b) report the results for the year-to-year effect of dryness on outcomes. Controls include AMC fixed effects, Macro-Region times year fixed effects and the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yields, each interacted with year dummies. Panels (c) and (d) report the results for the effects of decadal changes in dryness and exposure to dryness via banks on outcomes. Controls include macro-region fixed effects, the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yield. Capital outflows are measured as deposits minus loans divided by total assets. Hence, the effects for capital outflows are percentage point changes. Vertical lines are 90 percent confidence intervals.

Figure VIII: Effects of Excess Dryness on Migration Flows



Notes: The figure reports the estimated effects (in percentage points) on the net-, in- and out-migration rate between 2005 and 2010 for a municipality going from the 50th to the 90th percentile in the direct and indirect (exposure via migrant network) measures of excess dryness. Controls include macro-region fixed effects, the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yield. Vertical lines are 90 percent confidence intervals.

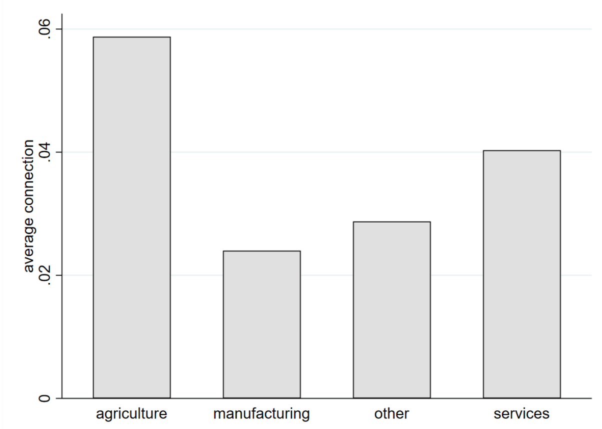
Figure IX: Effects of Excess Dryness on Employment by sector



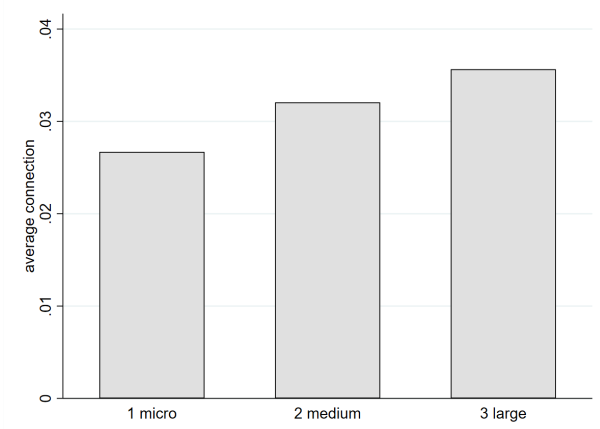
Notes: The figure reports the estimated effects on the log employment in each sector between 2000 and 2010 for a municipality going from the 50th to the 90th percentile in the direct and indirect (exposure via migrant network) measures of excess dryness. Controls include macro-region fixed effects, the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yield and exposure to Dryness via trade links. Vertical lines are 90 percent confidence intervals.

Figure X: Firm Initial Connections to High Excess Dryness Areas

(a) by sector



(b) by size



Notes: The figure shows the average connection $\alpha_{oi(m)}$ of firms to origins o that are in the top quartile of dryness by sector in plot (a) and by size in plot (b). The connection of firm i is calculated as the share of workers employed in the baseline year 2005 whose last observable move was from origin municipality o to the destination municipality m: $\frac{L_{i(m),t^*,o\to d}}{L_{i(m),t^*}}$.

Tables

Table I: Balance Test

Panel A: Number of reported droughts

	1(# Droughts =0)	1(# Droughts > 0)	Difference		t-stat
share of rural population	0.387	0.536	0.148	***	7.50
log income per capita	4.719	4.309	-0.410	***	3.88
alphabetization rate	0.768	0.661	-0.107	***	3.13
soy soil suitability	0.271	0.334	0.064	***	2.86
maize soil suitability	0.859	1.132	0.272	***	4.31
N observations	2,224	2,030			

Panel B: Dryness index

	1(Dryness $\leq$ median)	1(Dryness > median)	Difference	t-stat
share of rural population	0.440	0.477	0.037	1.47
log income per capita	4.570	4.478	-0.092	0.93
alphabetization rate	0.734	0.700	-0.035	1.24
soy soil suitability	0.285	0.317	0.031	1.33
maize soil suitability	0.951	1.028	0.078	1.05
N observations	2,127	2,127		

Notes: Observable characteristics observed in 1991 (pop census), except soy and maize productivity which are theoretical soy and maize yields under low inputs as defined in Bustos, Caprettini and Ponticelli (2016).

Table II: Reported Droughts and Excess Dryness

outcomes:	Number of droughts		
sample:	2000-2010	2011-2018	2000-2018
	(1)	(2)	(3)
Dryness	0.0796***	0.0730***	0.0699***
	(0.00915)	(0.0101)	(0.00736)
Observations	46,739	33,992	80,731
R-squared	0.507	0.738	0.620
Year and AMC FE	y	y	y
Macro-region x year FE	y	y	y
Controls x year FE	y	y	y
F-stat	480.4	223.4	567.6

Notes: Standard errors clustered at the microregion level (558) reported in parenthesis. F-stat is the Cragg-Donald Wald F statistic. Coefficient estimates refer to a municipality moving from the 50th to the 90th percentile of the distribution of dryness. The controls interacted with year dummies are the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yield.

Table III: Droughts, Excess Dryness and Agricultural Production 2000-2018

Panel A: Reported droughts, year-to-year effects

outcomes:	log area planted (1)	log area harvested (2)	log value production (3)
# droughts	-0.0259*** (0.00949)	-0.0535*** (0.0126)	-0.107*** (0.0119)
Observations	79,758	79,758	79,758
R-squared	0.934	0.919	0.923
Year and AMC FE	y	y	y
Macro-Region x year FE	y	y	y
Controls x year FE	y	y	y

Panel B: Excess dryness, year-to-year effects

outcomes:	log area planted (1)	log area harvested (2)	log value production (3)
Dryness	-0.0639*** (0.00997)	-0.0747*** (0.0110)	-0.0604*** (0.0111)
Observations	79,758	79,758	79,758
R-squared	0.934	0.919	0.923
Year and AMC FE	y	y	y
Macro-Region x year FE	y	y	y
Controls x year FE	y	y	y

Panel C: Excess dryness, long run effects (2000 to 2018)

outcomes:	Δ log area planted (1)	Δ log area harvested (2)	Δ log value production (3)
Avg Dryness, 2001-2018	-0.142*** (0.0439)	-0.171*** (0.0447)	-0.225*** (0.0494)
Observations	4,187	4,187	4,187
R-squared	0.235	0.254	0.238
Macro-Region FE	y	y	y
Controls	y	y	y

Notes: Standard errors clustered at the microregion level (558) reported in parenthesis. Coefficient estimates in Panels B and C refer to a municipality moving from the 50th to the 90th percentile of the distribution of dryness. Controls include: the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yields.

Table IV: Year-to-year Effects of Excess Dryness on Capital Flows 2000-2018

outcomes:	log loans			log deposits	net capital flows
	all	agri	non-agri		
	(1)	(2)	(3)	(4)	(5)
Dryness	0.0354***	0.0787***	0.0110	0.00535	0.0149***
	(0.00729)	(0.0153)	(0.00695)	(0.00426)	(0.00384)
Exposure to Dryness via banks	-0.0142*	-0.0685***	0.00364	0.00149	-0.0115***
	(0.00760)	(0.0195)	(0.00662)	(0.00412)	(0.00295)
Observations	58,124	50,606	58,124	58,124	58,124
R-squared	0.960	0.878	0.966	0.979	0.795
Year and AMC FE	y	y	y	y	y
Macro-Region x year FE	y	y	y	y	y
Controls x year FE	y	y	y	y	y

Notes: Standard errors clustered at the microregion level (558) reported in parenthesis. Coefficient estimates refer to a municipality moving from the 50th to the 90th percentile of the distribution of dryness or exposure to dryness via banks. Controls include: the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yields.

Table V: Decadal effect of Dryness on Capital Flows 2000-2010

outcomes:	log loans			log deposits	net capital flows
	all	agri	non-agri		
	(1)	(2)	(3)	(4)	(5)
Avg Dryness, 2001-2010	-0.118***	-0.0593	-0.104***	-0.0126	-0.0393**
	(0.0291)	(0.0532)	(0.0269)	(0.0206)	(0.0164)
Exposure to Dryness via banks	-0.0691***	-0.0603	-0.0484**	-0.0267*	-0.0132*
	(0.0187)	(0.0427)	(0.0195)	(0.0144)	(0.00708)
Observations	2,795	2,334	2,795	2,795	2,795
R-squared	0.167	0.158	0.168	0.185	0.062
Macro FE	y	y	y	y	y
Controls	y	y	y	y	y

Notes: Standard errors clustered at the microregion level (558) reported in parenthesis. Coefficient estimates refer to a municipality moving from the 50th to the 90th percentile of the distribution of dryness or exposure to dryness via banks. Controls include: the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yields.

Table VI: Migration Flows
2005-2010

outcomes:	net migration flows			outflows	inflows
	(1)	(2)	(3)	(4)	(5)
Avg Dryness, 2001-2010	-0.00898***	-0.0144***	-0.0145***	0.0115***	-0.00289
	(0.00249)	(0.00297)	(0.00296)	(0.00187)	(0.00241)
Exposure to Dryness via migrants		0.00816***	0.00824***	0.00130	0.00947***
		(0.00206)	(0.00207)	(0.00151)	(0.00159)
Exposure to Dryness via banks			-0.000532		
			(0.00162)		
Observations	4,248	4,248	4,248	4,248	4,248
R-squared	0.224	0.229	0.229	0.207	0.297
Macro-region FE	y	y	y	y	y
Controls	y	y	y	y	y

Notes: Standard errors clustered at the microregion level (558) reported in parenthesis. Coefficient estimates refer to a municipality moving from the 50th to the 90th percentile of the distribution of dryness or exposure to dryness. Controls include: the share of population living in rural areas, log income per capita, literacy rate, population density, changes in soy and maize potential yields and exposure to Dryness via trade links.

Table VII: Decadal Effect of Dryness on Employment 2000-2010

outcomes:	Δ log Employment						
	all sectors			agriculture	manufacturing	services	other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Avg Dryness, 2001-2010	-0.0150**	-0.0278***	-0.0289***	-0.0728***	0.0570**	-0.0554***	-0.0318***
	(0.00708)	(0.00815)	(0.00817)	(0.0155)	(0.0246)	(0.0101)	(0.0103)
Exposure to Dryness via migrants		0.0192***	0.0210***	0.0287***	0.0118	0.0217***	0.0312***
		(0.00607)	(0.00609)	(0.0109)	(0.0185)	(0.00783)	(0.00748)
Exposure to Dryness via banks			-0.0134***	0.0139	-0.0940***	-0.00269	-0.0136**
			(0.00462)	(0.00891)	(0.0174)	(0.00619)	(0.00686)
Observations	4,248	4,248	4,248	4,248	4,241	4,248	4,248
R-squared	0.128	0.132	0.134	0.071	0.099	0.093	0.049
Macro-region FE	y	y	y	y	y	y	y
Controls	y	y	y	y	y	y	y

Notes: Standard errors clustered at the microregion level (558) reported in parenthesis. Coefficient estimates refer to a municipality moving from the 50th to the 90th percentile of the distribution of dryness or exposure to dryness. Controls include: the share of population living in rural areas, log income per capita, literacy rate, population density, changes in soy and maize potential yields and exposure to Dryness via trade links.

Table VIII: Decadal Effect of Dryness on Population and Wages 2000-2010

outcomes:	Δ log Population		Δ log Avg Wages	
	(1)	(2)	(3)	(4)
Avg Dryness, 2001-2010	-0.0517***	-0.0525***	0.0120	0.0129
	(0.00692)	(0.00689)	(0.00817)	(0.00831)
Exposure to Dryness via migrants	0.0217***	0.0230***	0.0118*	0.0104
	(0.00455)	(0.00459)	(0.00665)	(0.00679)
Exposure to Dryness via banks		-0.0100***		0.00868
		(0.00363)		(0.00533)
Observations	4,248	4,248	4,248	4,248
R-squared	0.208	0.210	0.166	0.167
Macro-region FE	y	y	y	y
Controls	y	y	y	y

Notes: Standard errors clustered at the microregion level (558) reported in parenthesis. Coefficient estimates refer to a municipality moving from the 50th to the 90th percentile of the distribution of dryness or exposure to dryness. Controls include: the share of population living in rural areas, log income per capita, literacy rate, population density, changes in soy and maize potential yields and exposure to Dryness via trade links. In columns (3) and (4), we additionally control for the initial share of minimum wage earners in each municipality to capture the differential impact of the increase in the federal minimum wage in Brazil during the 2000-2010 decade.

Table IX: Workers' Flows to Firms Exposed to Dryness

outcomes:	$\frac{L_{oi(d)2006-2010}}{Lavg_i}$								
	All firms			by Sector			by Size		
				agri	manuf	services	small	medium	large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
firm connection to origin × 1(SPEI-12 < p25)		0.209***	0.322***	0.486***	0.369***	0.350***	0.657***	0.444***	0.255***
		(0.0375)	(0.0480)	(0.0798)	(0.0738)	(0.0484)	(0.0494)	(0.0351)	(0.0545)
firm connection to origin	0.621***	0.424***	0.506***	0.561***	0.436***	0.502***	0.388***	0.479***	0.529***
	(0.0132)	(0.0156)	(0.0198)	(0.0470)	(0.0213)	(0.0285)	(0.0174)	(0.0167)	(0.0224)
1(SPEI-12 < p25)		-0.139***	-0.132***	-0.112***	-0.135***	-0.179***	-0.193***	-0.145***	-0.122***
		(0.0164)	(0.0153)	(0.0160)	(0.0142)	(0.0203)	(0.0178)	(0.0145)	(0.0156)
Observations	1,415,758	1,415,758	1,415,758	67,756	248,742	983,990	478,006	711,306	223,730
R-squared	0.257	0.356	0.663	0.612	0.662	0.675	0.561	0.610	0.683
destination AMC FE	y	y	y	y	y	y	y	y	y
origin FE	y	y	y	y	y	y	y	y	y
firm FE	n	n	y	y	y	y	y	y	y

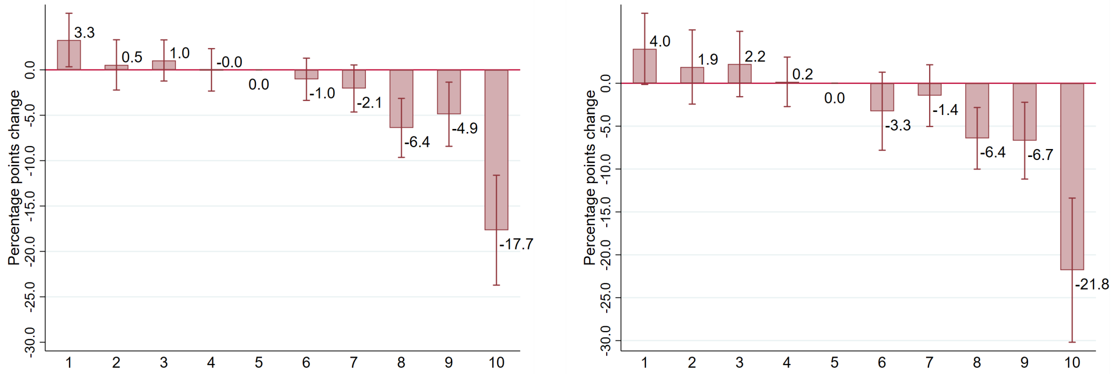
Notes: Standard errors clustered at destination municipality reported in parenthesis. The firm connection to origin is calculated as the share of workers employed in the baseline year 2005 in firm i whose last observable move was from origin municipality o to the destination municipality m: $\frac{L_{i(m),t^*,o\rightarrow d}}{L_{i(m),t^*}}$.

Appendix for: "The Effects of Climate Change on Labor and Capital Reallocation"

For Online Publication

Figure A1: Effects of Excess Dryness on Area Farmed and Area Harvested By Decile of Dryness

(a) Area Planted Area Harvested

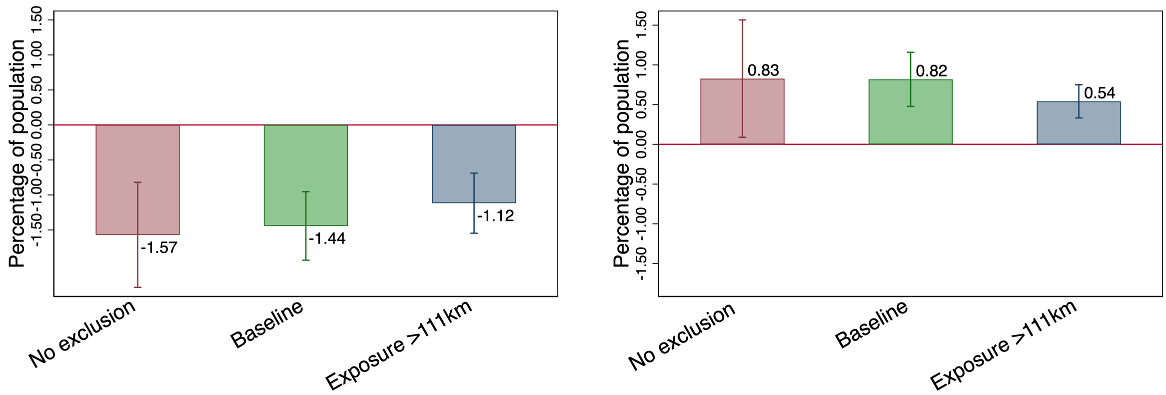


Notes: The figure shows the estimated coefficients on dummies capturing deciles of the excess dryness index in a panel regression at municipality-year level for the period 2000 to 2018. Deciles of *Dryness* go from the wettest to the driest. Estimated effects are relative to the 5^{th} decile. Controls include AMC fixed effects, macro-region times year fixed effects and the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yields, each interacted with year dummies. Vertical lines are 90 percent confidence intervals.

Figure A2: Effects of Excess Dryness on the net migration rate
Diagnostics on Spatial Correlation

(a) Direct effect

(b) Indirect effect



Notes: The figure reports the estimated effects on the net migration flow relative to population during the 2005 to 2010 period for a municipality going from the 50th to the 90th percentile in the direct and indirect (exposure via migrant network) measures of excess dryness. We report the estimated coefficients and confidence intervals for three alternative specifications: using the exposure via migrants without excluding any nearby municipalities (no exclusion), using our baseline measure excluding those within a $55km$ radius (the distance between grid points at which the raw data of the SPEI is available), and using the measure excluding those within a $111km$ radius. Controls include macro-region fixed effects, the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yield. Vertical lines are 90 percent confidence intervals.

Table A1: Correlation Between Measures of Exposure via migrants, via banks and via trade links

	Dryness	Exposure via banks	Exposure via migrants	Exposure via trade links
Dryness	1.000			
Exposure via banks	0.110	1.000		
	0.000			
Exposure via migrants	0.643	0.157	1.000	
	0.000	0.000		
Exposure via trade links	0.438	0.364	0.303	1.000
	0.000	0.000	0.000	

Notes: All measures of exposure are computed excluding 55km area around focal AMC

Table A2: Coefficients on Exposure to Dryness via Trade Links 2000-2010

outcomes:	Capital net flows (1)	Δ log loans (2)	Migration net flows (3)	Δ log L (4)	Δ log wage (5)
Exposure to Dryness via banks	-0.0404*	-0.217***	-0.000532	-0.0134***	0.00639
	(0.0214)	(0.0562)	(0.00162)	(0.00462)	(0.00542)
Exposure to Dryness via migrants	0.0290*	0.107***	0.00824***	0.0210***	0.0133**
	(0.0174)	(0.0312)	(0.00207)	(0.00609)	(0.00668)
Exposure to Dryness via trade links	0.0601*	-0.0241	-0.00983***	0.00123	-0.00532
	(0.0309)	(0.0544)	(0.00352)	(0.0112)	(0.0116)
Observations	2,795	2,795	4,248	4,248	4,248
R-squared	0.066	0.172	0.229	0.134	0.165
Macro-region FE	y	y	y	y	y
Controls	y	y	y	y	y

Notes: Standard errors clustered at the microregion level (558) reported in parenthesis. Coefficient estimates refer to a municipality moving from the 50th to the 90th percentile of the distribution of dryness or exposure to dryness. Controls include: the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yields.

Table A3: Robustness of Capital Effects to Clustering at Mesoregion level

Panel A: Year-to-Year Effects

outcomes:	log loans			log deposits	net capital flows
	all	agri	non-agri		
	(1)	(2)	(3)	(4)	(5)
Dryness	0.0354***	0.0787***	0.0110	0.00535	0.0149***
	(0.00868)	(0.0201)	(0.00921)	(0.00709)	(0.00484)
Exposure to Dryness via banks	-0.0142	-0.0685**	0.00364	0.00149	-0.0115***
	(0.0117)	(0.0310)	(0.0102)	(0.00610)	(0.00440)
Observations	58,124	50,606	58,124	58,124	58,124
R-squared	0.960	0.878	0.966	0.979	0.795
Year and AMC FE	y	y	y	y	y
Macro-Region x year FE	y	y	y	y	y
Controls x year FE	y	y	y	y	y

Panel B: Decadal Effects

outcomes:	Δ log loans			Δ log deposits	Δ net capital flows
	all	agri	non-agri		
	(1)	(2)	(3)	(4)	(5)
Avg Dryness, 2001-2010	-0.118***	-0.0593	-0.104***	-0.0126	-0.0393*
	(0.0371)	(0.0692)	(0.0336)	(0.0255)	(0.0226)
Exposure to Dryness via banks	-0.0691**	-0.0603	-0.0484	-0.0267	-0.0132
	(0.0271)	(0.0694)	(0.0321)	(0.0254)	(0.0108)
Observations	2,795	2,334	2,795	2,795	2,795
R-squared	0.167	0.158	0.168	0.185	0.062
Macro-Region FE	y	y	y	y	y
Controls	y	y	y	y	y

Notes: Standard errors clustered at the mesoregion level (115) reported in parenthesis. Coefficient estimates refer to a municipality moving from the 50th to the 90th percentile of the distribution of dryness or exposure to dryness via banks. Controls include: the share of population living in rural areas, log income per capita, literacy rate, population density and changes in soy and maize potential yields.

Table A4: Robustness of Migration and Employment Effects to Clustering at Mesoregion level

outcomes:	net mig. flows	Δ log Employment				
		all sectors	agriculture	manufacturing	services	other
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Dryness, 2001-2010	-0.0145***	-0.0289***	-0.0728***	0.0570*	-0.0554***	-0.0318**
	(0.00374)	(0.00949)	(0.0211)	(0.0324)	(0.0144)	(0.0145)
Exposure to Dryness via migrants	0.00824***	0.0210***	0.0287**	0.0118	0.0217***	0.0312***
	(0.00237)	(0.00621)	(0.0142)	(0.0196)	(0.00787)	(0.00803)
Exposure to Dryness via banks	-0.000532	-0.0134**	0.0139	-0.0940***	-0.00269	-0.0136*
	(0.00195)	(0.00595)	(0.0113)	(0.0234)	(0.00824)	(0.00808)
Observations	4,248	4,248	4,248	4,241	4,248	4,248
R-squared	0.229	0.134	0.071	0.099	0.093	0.049
Macro-region FE	y	y	y	y	y	y
Controls	y	y	y	y	y	y

Notes: Standard errors clustered at the mesoregion level (115) reported in parenthesis. Coefficient estimates refer to a municipality moving from the 50th to the 90th percentile of the distribution of dryness or exposure to dryness. Controls include: the share of population living in rural areas, log income per capita, literacy rate, population density, changes in soy and maize potential yields and exposure to Dryness via trade links.

Table A5: Robustness of Population and Wage Effects to Clustering at Mesoregion level

outcomes:	Δ log Population		Δ log Avg Wages	
	(1)	(2)	(3)	(4)
Avg Dryness, 2001-2010	-0.0517***	-0.0525***	0.0120	0.0129
	(0.0106)	(0.0102)	(0.0119)	(0.0123)
Exposure to Dryness via migrants	0.0217***	0.0230***	0.0118	0.0104
	(0.00504)	(0.00504)	(0.00818)	(0.00843)
Exposure to Dryness via banks		-0.0100*		0.00868
		(0.00516)		(0.00795)
Observations	4,248	4,248	4,248	4,248
R-squared	0.208	0.210	0.166	0.167
Macro-region FE	y	y	y	y
Controls	y	y	y	y

Notes: Standard errors clustered at the mesoregion level (115) reported in parenthesis. Coefficient estimates refer to a municipality moving from the 50th to the 90th percentile of the distribution of dryness or exposure to dryness. Controls include: the share of population living in rural areas, log income per capita, literacy rate, population density, changes in soy and maize potential yields and exposure to Dryness via trade links. In columns (3) and (4), the share of minimum wage earners is included additionally.