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THE EFFECTS OF CLIMATE CHANGE ON LABOR AND CAPITAL REALLOCATION

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ABSTRACT

We study the effects of climate change on labor and capital reallocation across regions, sectors and firms. We use newly digitized administrative reports on extreme weather events occurred in Brazil during the last two decades and a meteorological measure of excess dryness relative to historical averages to estimate the effects of droughts in the local economy of affected areas, on the magnitude of the labor and capital flows they generate and on factor allocation in destination regions. We document two main results. 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 capital outflows driven by a reduction in loans, consistent with a permanent decrease in investment opportunities. Second, we find that abnormal dryness affects the structure of both the local economy and the economy of areas connected via migrant networks. Directly affected areas experience a sharp reduction in population and employment, concentrated in agriculture and services. While local manufacturing absorbs some of the displaced workers, these regions experience large out-migration flows. Regions receiving climate migrants expand employment in agriculture and services, but not in manufacturing. Using social security data, we provide evidence that labor market frictions direct migrants to firms connected to migrant social networks, which are mostly outside the manufacturing sector. This has implications for the composition of economic activity and the firm size distribution in destination regions.

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I Introduction

The speed of observed 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, is expected to increase (Hsiang and Kopp, 2018). 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 (Mani et al., 2018). Empirical evidence shows that increases in temperature and extreme weather events have negative effects on local economic activity and can generate migration away from affected areas (Dell et al., 2014). However, we lack a clear understanding of how the process of reallocation of economic activity away from areas affected by climate change can mitigate its effects. In particular, there is scarce empirical evidence on the effects of factor reallocation originated by climate change on destination regions.

In this paper, we use new data on extreme weather events that occurred in Brazil during the last two decades to estimate their effects on the local economy of the affected areas, on the magnitude and direction of labor and capital movements that they generate, and on the allocation of factors across sectors and firms in destination regions.

To measure extreme weather events, such as droughts, we digitized administrative data from the National System of Civil Protection in Brazil (Sistema Nacional de Proteçao e Defesa Civil - SINPDEC), which records every reported natural disaster at the municipality-level. These data are based on requests of aid from the federal government and, thus, might be subject to reporting bias. To overcome this concern, we use a meteorological measure of droughts, the Standardized Precipitation Evapotranspiration Index (SPEI). This index measures the moisture deficit in a given location relative to its 100 year average and is based on local precipitation and temperature data. It is used by climatologists to predict droughts, including those caused by climate change (Vicente-Serrano et al., 2010). Indeed, we find that this index is a strong predictor of the drought events reported in the SINPDEC data. The SPEI also shows an increase in abnormally dry conditions across Brazilian regions during the last twenty years relative to historical averages, consistent with the increase in average temperatures. We complement these data with information from the Population Census, which records the municipality of origin of all internal migrants in Brazil; social security data from the Annual Social Information System (RAIS), which permits to track workers across regions, sectors and firms; and balance sheet data from all bank branches in Brazil (ESTBAN), which permits to track capital flows across regions.

First, we document that regions subject to dry meteorological conditions in a given year experience a sharp reduction in agricultural output but receive capital inflows: local bank deposits contract, while bank loans expand. Funds are partly drawn from areas connected to affected regions through bank branch networks, which experience capital outflows. 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 unusually dry meteorological conditions, we find that affected regions experience capital outflows, driven by a reduction in loans to these areas. More specifically, a region experiencing unusual dryness during a decade (defined as an increase in average decadal dryness of about 0.5 of a standard deviation relative to its 100 year mean), suffers a 13.3 percent decline in lending originated by local branches. 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 productivity.

Second, we find that areas with a higher incidence of droughts during the decade 2000-2010 experienced a sharp reduction in population and agricultural employment. This led to a change in the structure of the local economy, where manufacturing employment expanded while the service sector contracted. These findings suggest that the fall in agricultural productivity reduced the demand for local non-traded goods such as services, while it generated an expansion in local traded goods such as manufacturing by reducing the price of labor. However, not all displaced workers were absorbed locally: we document large out-migration flows from both rural and urban areas affected by droughts. In particular, a region experiencing unusual dryness during a decade (defined as an increase in average decadal dryness of 0.5 of a standard deviation relative to its 100 year mean), suffers a population loss of 5.7 percent.

Next, we track the destination of climate migrants. For this purpose, we use the fact that workers who migrate are more likely to relocate towards regions where they have social networks, measured by historical migration links. Then, we construct a measure of indirect exposure of each destination to droughts by summing the droughts that occurred 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. We find that regions receiving climate migrants expand employment in agriculture and services, but not in manufacturing. In particular, a region where 10 percent of historical migrants came from areas affected by unusual dryness during the present decade, experiences an increase in agricultural employment of 0.85 percent and a reduction in manufacturing employment of 0.53 percent.

This finding might be driven by the fact that climate migrants lack the skills required for employment in manufacturing in urban areas. 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 explanations next.

To shed some light on the assignment process of climate migrants to jobs at destination, we use the social security data to bring the analysis to the firm-level. For each firm, we construct a measure of exposure to climate migrants. First, we measure whether a firm is connected to regions experiencing droughts through social networks by the baseline share of workers in the firm coming from origins with high exposure to droughts. We find that workers from drought areas 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, labor market frictions direct migrants to connected firms. This has important implications for the composition of economic activity in destination regions.

First, we document that the manufacturing sector is the least connected to drought areas through past migrant networks: only 2 percent of its workers come from those areas compared to 4 percent in services and 6 percent in agriculture. This might reflect the fact that manufacturing is geographically concentrated due to agglomeration economies. Second, in a given destination, the estimated elasticity of worker inflows from connected origins experiencing droughts are three times larger for firms in the agricultural sector than for firms in manufacturing. This implies that even in the presence of referral networks, manufacturing firms are less prone to employ workers coming from drought areas. This might be due to the fact that manufacturing firms require specialized skills that are sourced in thick local labor markets. Indeed, we find that migrants from drought areas have lower levels of education and earnings than comparable workers at destination.[1] Third, we find that the estimated elasticity of worker inflows from connected origins experiencing droughts is twice as large 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.[2]

Let us emphasize that a higher incidence of droughts in some locations can have effects in other locations through several channels other than migration flows. For example, goods trade can generate demand or supply linkages across regions. Similarly, droughts can generate capital flows across regions, as we discussed above. If regions with larger labor market integration are also more linked through goods or capital markets, then our measure of labor market integration, namely migrant networks, could capture these other channels. We address this concern by exploiting the fact that 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 through labor, product and capital market linkages. In

[1] In contrast, migrants from areas with average weather tend to have a similar level of education as comparable workers at destination.

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

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. In particular, we check whether our estimated elasticity of firm labor flows from drought origins is affected by the inclusion of firm fixed effects. We find that this elasticity increases by 50 percent when we control for firm-fixed effects, suggesting that the positive effects of labor market linkages on the level of employment might be partly reduced by negative effects of goods market linkages. This would be the case if firms more connected to a particular origin through migrant networks are also more connected through commercial networks and suffer from a lower demand for their products or lower supply (higher prices) for their inputs.

When we control for both destination municipality and firm fixed effects to absorb the capital and goods market channels, our estimates indicate that a firm in agriculture with average connection to areas highly affected by droughts experience a 7 percent larger flow of workers from such regions when the number of droughts at origin increases by 2.62 – the difference between the average number of droughts in the top quartile and the rest of the distribution – in the 2006-2010 period. This effect is about three times larger than the one observed for firms in manufacturing (2.3 percent), while the effect on firms in services is 1.2 percent.

This paper attempts to contribute to the literature measuring the potential effects of climate change on economic outcomes. There is a rich empirical literature showing that weather shocks have negative effects on local economic activity and can generate migration away from affected areas (Jayachandran, 2006; Schlenker and Roberts, 2009; Deschênes and Greenstone, 2007; Dell et al., 2012; Hornbeck, 2012). We contribute to this literature by providing direct empirical evidence on the spillover effects of these local shocks into other locations integrated through labor and capital markets. We expect that our estimates can also be informative for the recent quantitative trade and spatial models studying the effects of climate change on productivity and the spatial allocation of population and economic activity (Desmet and Rossi-Hansberg, 2015; Costinot et al., 2016; Balboni, 2019; Conte et al., 2020).

II Climate Change and Droughts 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. As climate has warmed over recent years, a new pattern of more frequent and more intense weather events has emerged across the world. Recent attribution studies show that the warming climate made several recent extreme weather events more severe and 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).

Temperature increases have been steeper in tropical countries such as Brazil. Figure I use data from the Climatic Research Unit 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, with an acceleration in the trend since 1980. 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, as climate change makes these events more likely, understanding the economic effects of extreme weather events can be informative about the potential effects of climate change.

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 (panel a) and 2011-2018 period (panel b).

As the SINPDEC data could suffer from reporting biases across municipalities or time, we also use 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 compares the amount of precipitation in a given area with its evapotranspiration needs, which are a function of temperature. As a result, it 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.

Figure IV shows the time series of monthly SPEI in Brazil between 1905 to 2018.[3]

[3] In this Figure as in the rest of the empirical analysis we use the SPEI-12, the version of SPEI computed at a 12 months time scale.

The index captures deviation in dryness relative to the average observed during the whole 1905-2018 period. A value of SPEI equal to -1 can be interpreted as the difference between rain and potential evapotranspiration needs being one standard deviation lower than the historical average for a given locality during that period.[4] The figure shows an increase in the incidence of droughts since 2012, confirming the upward trend in reports seen in Figure II. Figure III shows the geographical distribution of SPEI across Brazil in the 2000-2010 period (panel c) and 2011-2018 period (panel d).

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

$$SPEI_{jm} = \alpha + \sum_{k=-12}^{12} \beta_k drought_{jm}^{k} + \varepsilon_{jm}, \quad (1)$$

where j indexes municipalities, m indexes calendar months, and k indexes months relative to a reported drought in the SINPDEC data. The variable $drought_{jm}^{k}$ is a dummy equal to 1 if municipality j is k months away from a reported drought in the SINPDEC data, 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 V plots the coefficients β_k. As shown, the deviation of SPEI from its mean is the lowest in the month a drought is reported (around 0.7 below its mean). The figure also shows that dry weather is registered well ahead of the month a drought is reported, starting to be significantly below the mean around four months earlier. This suggests that the incidence of dry weather over several months is what usually triggers a report. Furthermore, the SPEI continues to be low during several months after the report, still being around 0.4 below the mean six months after a drought event is reported.

III Empirical Analysis

In this section, we study the effects of reported droughts and unusually dry meteorological conditions as captured by the SPEI on economic outcomes. First, we analyze the effect of local contemporaneous weather shocks on local agricultural output. Second, we study the effects of both contemporaneous droughts and a full decade of unusually dry meteorological conditions on deposits and loans by local bank branches. Next, we track the destination of capital flows originated by droughts through the bank branch network. Third, we study the effects of droughts on labor flows across regions and sectors using

[4] 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.

data from the population Census. Finally, we track formal worker flows across regions, sectors, and firms using social security data from RAIS.

III.A Agricultural Production

III.A.1 Specification

We begin by estimating the effects of reported droughts and excess dryness as captured by SPEI on agricultural outcomes at the yearly level with the following specification:

$$y_{ot} = \alpha_o + \alpha_t + \beta_1 Dryness + \Lambda Controls_{ot} \times t + u_{ot}, \tag{2}$$

where o indexes municipalities, and *Dryness* is either the number of droughts reported in SINPDEC or SPEI. To ease the comparison between the specifications with reported droughts and SPEI, we henceforth always use the latter multiplied with -1, so that an increase in either measure is associated with higher dryness. We will interchangeably refer to SPEI $\times(-1)$ as "excess dryness".

The vector of controls includes the share of adults living in rural areas in 1991, the geographical distance to the coast (both interacted with year dummies) and the number of floods reported in the SINPDEC dataset.[5] To study the impact of dryness on agricultural production, we consider the following outcome variables: log area planted, log area harvested, and the log value of agricultural production. The outcome variables are sourced from the Agricultural Production Survey (PAM).[6] We run the regression first on a sample including the time period 2000-2010, which corresponds to the years we consider in our subsequent empirical analysis based on Census data. We then also consider the sample comprising the time period 2011-2018. As can be seen in Figure IV, this is a period of much more severe dryness in Brazil, which we are able to include in our analysis using social security data up to 2018 in Section III.E.1.

III.A.2 Results

The estimates of β_1 for each of the two sub-periods are presented in Table II. Using reported droughts as the regressor in Panel A and considering the period 2000-2010 in the first three columns, we find no significant effect on the area planted but a significant negative effect on the area harvested: an additional reported drought is associated with a decrease by 4.1 percent. The value of the agricultural production falls even by 9.2 percent, more than twice as much as the harvested area. Consistent with the much higher severity

[5]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.

[6]PAM Survey is carried out by the Brazilian Statistical Institute (IBGE) at yearly frequency. It covers the 31 major temporary crops and the 33 major permanent crops farmed in Brazil.

of droughts in the second period, we find more negative effects and also a significant decrease in the area planted of almost 6 percent when considering the 2011-2018 sample in the final three columns. The losses in harvested area and production value are 8.8 and 13.5 percent, respectively.

In Panel B, we estimate equation (2) using SPEI as a measure of dryness. We find that an increase in excess dryness by one standard deviation (i.e. an increase in the SPEI$\times(-1)$ by 1) decreases the area planted by 1.6 percent and the area harvested by 2.7 percent during 2000-2010. Consistent with the results in Panel A, the effect on the production value is around twice as large as the effect on the harvested area (5.2 percent). During the 2011-2018, the negative impact of dryness is again much stronger for all three outcome variables, with the loss of harvested area being 7 percent and the loss of production value being 7.4 percent.

Overall, these estimates suggest that higher dryness, both when reported and measured using weather data, is associated with sizable output losses in the agricultural sector. This holds true during both periods we consider, with the negative impact of dryness being significantly stronger during the 2010s.

III.B Capital Reallocation

III.B.1 Specification

In this section, we study the impact of climate change 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 begin by estimating a yearly regression as the one described in equation (2). We use this specification to study the contemporaneous effects of dryness conditions on local deposits, loans and capital outflows. We define the latter for each municipality as the difference between total deposits and total loans, normalized by assets.

We also investigate the indirect effects on regions linked to those affected by drought events or excess dryness via bank branch networks. To this end, we construct a measure of municipality-level exposure to dryness in connected regions based on Bustos et al. (2020). This measure is constructed in two steps. First, we define the degree of exposure of each bank to drought events or excess dryness based on the geographical structure of its bank branch network as follows:

$$BankExposure_{bt} = \sum_{o \in O_b} \omega_{bo} \lambda_{TAo} Dryness_{ot}. \tag{3}$$

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 at baseline, and λ_{TAo} is the share of land employed by the agricultural sector in the origin o.[7] Next, we define the municipality-level exposure to drought events or excess dryness via bank branch networks as follows:

$$MunicipalityExposure_{dt} = \sum_{b \in B_d} w_{bd} BankExposure_{bt}, \tag{4}$$

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. To investigate the indirect effects of climate change, we therefore include the yearly measure of municipality exposure described in (4) into the specification described in equation (2).

Finally, we study the long-term effects of direct and indirect exposure to drought events or excess dryness by estimating a specification like the one described in equation (6), and focus on decadal changes in deposits, loans and capital outflows between 2000 and 2010 as outcomes.

III.B.2 Results

We start by documenting the contemporaneous effects of droughts and excess dryness conditions on capital outcomes. The results are reported in Table III. As in section III.A, dryness is measured as number of reported drought events in a given year in Panel A, and as the yearly average of SPEI-12 multiplied with -1 in Panel B.

To quantify the coefficients, we inspect the distribution of reported droughts and SPEI across municipalities, and compute the predicted percentage change in capital outcomes when a municipality moves from the median value in the distribution to an extreme value, for which we take the 90th percentile. In the distribution of reported droughts per year, the median municipality had no droughts, while the municipality at the 90th percentile reported 1 drought. Similarly, a move from the median to the 90th percentile of the SPEI-12 $\times(-1)$ implies an increase in the excess dryness index of 0.93, which corresponds to about one standard deviation higher dryness relative to the historical average for a given municipality.

In column (1) we focus on the direct effects on local deposits. We find that municipalities with one reported drought experienced a 1.2 percent decline in local bank deposits relative to municipalities with no reported droughts. We find a similar effect in Panel B,

[7] Data on agricultural land at municipality level is from the 1996 Agricultural Census. We use this weight to capture the exposure of the local economy to climate events.

where the coefficient on SPEI-12 $\times(-1)$ indicates that a standard deviation increase in excess dryness corresponds to a decline in local deposits of about 0.5 percent. The result on deposits is consistent with individuals in areas directly affected by droughts or excess dryness using their savings to cope with the negative impact on climate shocks.

In column (2) we study the effects on loans originated by local branches. As shown, an increase in reported droughts is associated with a decline in loans (1.7 percent), while an increase in extreme dryness is associated with an increase in loans originated by local branches of about 1.4 percent. Variation in reported droughts is likely to also capture variation in federal transfers received from the central government. These directed transfers are designed to help local communities absorb the negative impact of climate shocks, reducing the need for individuals and firms to borrow when negatively impacted by climate events. On the other hand, the SPEI-12 measure captures to what extent a region is experiencing a period of abnormal dryness, irrespective of whether local officials decide to file a request for financial support to the federal government. As such, we interpret the positive coefficient on SPEI-12 as capturing the role of financial markets to allow risk sharing and consumption smoothing for individuals and firms hit by negative climate shocks.

In column (3), we focus on capital outflows, captured by the difference between deposits and loans and normalized by the value of assets. A positive value of capital outflows implies that a given municipality is a net exporter of capital in the formal banking network, while a negative value implies that local lending is financed with capital imported from other regions. We find a negative and significant effect of excess dryness on capital outflows, which indicates that regions experiencing abnormally dry conditions tend to be net importers of capital via the banking sector. The magnitude of the coefficient indicates that municipalities with one standard deviation higher excess dryness experienced, on average, a 1.6 percentage points larger inflow of capital as a share of assets of local bank branches. The coefficient on reported droughts is negative but not significant, potentially due to the effect of transfers described above.

Finally, we add to our specification the indirect effect of droughts and excess dryness in regions connected via the bank network using the measure described in equation (4). We find that regions connected via the bank network to areas experiencing excess dryness episodes tend to be net exporters of capital. In particular, a region whose indirect exposure to excess dryness via the bank network increases from the median to the 90th percentile (an increase of 0.07 in municipality exposure) experiences capital outflows of about 0.3 percentage points of assets of its local bank branches. Overall, our results at the yearly level indicate that regions directly affected by climate shocks import capital to allow local individuals and firms to cope with such shocks, while regions connected via the bank network export capital to provide the funds necessary for this risk sharing activity.

In the remainder of this section, we investigate the long-run effects of droughts and excess dryness on capital outcomes by running the following regression:

$$y_{dr,2000-2010} = \beta_1 Dryness_{dr,2001-2010} + \alpha_r + \gamma X_{dr} + \varepsilon_{dr}, \tag{5}$$

where α_r denotes macro-region fixed effects and X_{dr} is a set of controls for municipality characteristics. These include the share of population living in rural areas, income per capita, literacy rate, population density as well as the changes in soy and maize productivity.[8]

Table IV reports the results using as dependent variables the changes in deposits, loans and capital outflows between 2000 and 2010. We start by discussing the effects on deposits. As shown, we find that areas with higher incidence of droughts or with higher excess dryness over the 2000-2010 decade relative to their historical averages experience a decline in bank deposits, which is however not statistically significant at standard levels.

Next, in column (2), we focus on the long-run effects on lending. Our main result is that areas with higher excess dryness over the 2000-2010 decade experienced a larger and significant decline in loans originated by local banks. This result, coupled with the results presented in Table III, gives 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 indicates that the financial system redirects credit destined to finance investment outside of areas affected by abnormal climate. In particular, the magnitude of the coefficient in column (2) of Panel B indicates that a municipality whose average excess dryness in the 2000-2010 period increases from the median level to the 90th percentile (an increase of 0.45 in the index) experienced a 13.3 percent decline in lending originated by local bank branches.

The results in column (3) confirm this intuition, showing that in the long run areas experiencing abnormal dryness over the 2000-2010 decade also experienced larger capital outflows. The magnitude of the coefficient indicates that the direct effect of excess dryness for a municipality moving from the median to the 90th percentile of SPEI-12$\times(-1)$ is a 2.4 percentage points increase in capital outflows as a share of assets. In column (3) we also include the indirect effect of being connected with abnormally dry areas via the bank network. As shown, in the long run, regions connected to those directly affected by abnormally dry climate experience larger capital outflows. The magnitude of the coefficient indicates that a movement from the median to the 90th percentile of municipality-level exposure increases capital outflows by about 3.8 percent of assets. Notice that, in the long

[8] We use changes in soy and maize potential yields from Bustos et al. (2016) to control for the differential impact of new technologies introduced in Brazilian agriculture during the period under study.

run, connected regions might be negatively affected by abnormally dry climate at origin due to an overall decline in local capital supply. Such decline in capital can result from an out-migration of workers (which we document below in section III.C), and a general decline in long-run investment opportunities in the region.

III.C Labor Reallocation across Regions and Sectors

III.C.1 Specification

As a next step, we turn to Census data to analyze the impact of drought events on the reallocation of labor across regions and sectors. 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, droughts directly affect labor. We estimate this *direct effect* by using the average yearly number of reported local droughts during 2001-2010 or the average excess dryness as regressors.

Second, when a spatial reallocation of factors occurs, those regions that are not directly affected by dryness but destinations or origins of factors that move might also experience changes in their overall amount of labor. We refer to this mechanism as the *indirect effect.* To capture this effect for labor flows, we construct a measure of exposure of municipalities to droughts through migration links. For this, we assume that destinations that received a higher share of migrants (out of all migrants) from certain origins in the past (i.e. before the drought period) are more likely to receive migrants from these origins when droughts occur there than those destinations that had previously received a lower share of migrants from them. 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 use to construct internal migration flows based on a question asking repondents 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.[9] We then construct the exposure to dryness via migration links as

$$Exposure_{d,2001-2010} = \sum_{o \neq d} \alpha_{od} Dryness_{o,2001-2010},$$

with

$$\alpha_{od} = \frac{M_{1995-2000,o \to d}}{M_{d,2000}},$$

where o denotes the origin municipality, d the destination municipality, $M_{1995-2000,o \to d}$ the

[9] 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.

size of the migrant flow from o to d between 1995 and 2000, and $M_{d,2000}$ the total number of persons that migrated during this period to d.

Having created the measures for direct effects and indirect effects, we run the following regression:

$$y_{dr,2000-2010} = \beta_1 \underbrace{Dryness_{dr,2001-2010}}_{\text{Direct effect}} + \beta_2 \underbrace{Exposure_{dr,2001-2010}}_{\text{Indirect effect}} + \alpha_r + \gamma X_{dr} + \varepsilon_{dr}, \qquad (6)$$

where X_{dr} is the same set of controls for municipality characteristics as in Equation (5). As a first set of dependent variables, we use either the 2000-2010 log change in total working age population (18-64) or employment (total and per sector) in municipality d. As a second set of outcomes, we use municipalities' migration rates. In particular, we consider the net migration rate, calculated 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:

$$\frac{inflows_{d,2005-2010} - outflows_{d,2005-2010}}{population_{d,2010}}$$

Further, we also use in-migration and out-migration rates separately as dependent variables.

III.C.2 Results

Table V shows the regressions results of estimating (6) with the log change in population as the dependent variable. The first column presents the coefficients of a simplified specification including only the direct effect at origin and without controls apart from macro-region fixed effects. In the second and third column, we add the controls for municipality characteristics and the indirect effect through exposure, respectively. In the final two columns, we split the sample into primarily rural or urban municipalities according to whether the share of population living in rural areas is below or above the median.

Both when using reported droughts in Panel A or excess dryness in Panel B, we obtain a significant negative effect of dryness on population in all specifications in the first three columns. Controlling for municipality characteristics reduces the effect somewhat, in particular for reported droughts, while including exposure greatly increases it. Reported droughts have a larger negative effect on population in urban regions, while effects do not differ much between rural and urban regions when using excess dryness.

Looking at the indirect effects, we find an increase in population with higher exposure to dryness via previous migration links, and this effect is stronger in urban regions. We view this as confirmation for the importance of separately capturing direct and indirect effects, which are highly correlated due to the spatial clustering of weather shocks, implying that dry areas are more likely to be connected through migration links to other dry areas. Thus, the estimate of the direct population effect is biased upwards when considering local dryness only, if connected regions are more likely to receive migrants.

In order to quantitatively interpret the direct population effects implied by these regressions at the decadal level, we compute the population effect of going from the median to the 90th percentile implied by the coefficient in column (3) as $-0.0391 \times 0.7 = -0.027$. Thus, a municipality at the 90th percentile of reported droughts loses 2.7 percent of its population over ten years relative to a municipality at the median of the distribution (meaning zero reported droughts). A move from the median to the 90th percentile of the SPEI $\times(-1)$ implies an increase by 0.44. While this seems a rather small number given that the measure reached values above 2 during 2001-2010, note that such extreme values are smoothed through taking ten year averages. A value of 0.44 implies that dryness measured by the SPEI is on average almost half a standard deviation above its long-run mean over 120 consecutive months. Such a deviation certainly implies an exceptional period of dryness. The predicted population decline in a region experiencing such a period, which we obtain from the estimate in column (3) of Panel B, is 5.7 percent.

To quantify the indirect effect, we assume that 10 percent of the migrants that a municipality received during 1995-2000 come from origins that moved from the median to the 90th percentile of the distribution of our dryness measures. Therefore, the indirect effect on population implied by the coefficient in column (3) is $0.0599 \times 0.07 = 0.0042$ for droughts and $0.113 \times 0.044 = 0.0050$ for excess dryness.

In Table VI, we run the full specification with the change in total employment as the dependent variable and again obtain negative direct effects of reported droughts or excess dryness and positive indirect effects via exposure through migration links. The direct employment effect including all sectors shown in column (1) is quantitatively similar to that we obtained for population in Panel A. In Panel B, both the direct and indirect effects are somewhat smaller than in the comparable specification in column (3) of Table V. Moving from the 50th to the 90th percentile of excess dryness implies a decrease in employment of 3.9 percent, while the indirect effect due to 10 percent of migrant origins experiencing such an increase is predicted to increase employment by around 0.4 percent.

Columns (2)-(5) show the estimated effects on employment in the agricultural, manufacturing, service and the residual “other ”sectors (which includes the public sector, construction, extractive industry and utilities). In line with the negative impact on agricultural productivity we documented above, we find that agriculture is most negatively affected by dry weather. Interestingly, also the service and other sectors, which produce mostly non-tradable goods, see their employment decline, while the effect on manufacturing is zero in Panel A and slightly positive in Panel B. Looking at the indirect effects, we see that the three sectors with employment declines due to the direct effect are those that expand their employment when the indirect exposure to droughts via previous migration links increases. Hence, these findings strongly suggest that dry weather shocks lead to a reallocation of labor from affected to not directly affected (but connected) regions through migration of workers primarily in agriculture and non-tradable sectors. Further, in directly affected regions, some released workers are absorbed by an expansion of the manufacturing sector. Figure VI illustrates the results by sector shown in columns (2)-(5) of Panel B using bars that indicate the size of the effects computed with the above described quantification method. Moving from the 50th to the 90th percentile in excess dryness leads to a fall in agricultural employment by almost 11 percent and an increase in manufacturing employment by more than 8 percent. The indirect effect implies that agricultural employment expands by 0.85 percent, while manufacturing employment contracts by 0.53 percent.

Finally, to provide additional evidence on the extent to which internal migration is the driver of labor reallocation across regions, in Table VII we use the above described 2005-2010 migration rates as dependent variables. Consistent with the results on population and employment, we find negative effects of dry weather on the net migration rate in column (1). Columns (2) and (3) investigate whether the changes in net migration are driven by lower inflows or higher outflows and suggest that both the in-migration rate falls and the out-migration rates increases, although the effect on the latter is not significant when using reported droughts. The last two columns show that reported droughts decrease net migration rates more strongly in urban areas, while excess dryness decreases them by a similar amount in rural and urban areas. Again in line with the population results, the exposure measure has a positive effect on the net migration rate, which is entirely driven by higher inflows, as outflows are unaffected in Panel A and slightly positively affected in Panel B. This finding is to be expected, if exposed municipalities expand their population and employment through receiving migrants and these incoming migrants themselves crowd out some present workers, leading to positive effects on both in- and out-migration rates. Confirming the findings for population in Table V, the positive effect on the net migration rate is stronger in urban municipalities.

Figure VII visualizes the quantitative effects for the specification in Panel B with either the net migration rate (upper plots), in-migration rate (middle plots) or out-migration rate (bottom plots) as the dependent variable, using the full, the rural and the urban sample. The decomposition in inflows and outflows for the rural and urban subsamples suggests that both rural and urban municipalities receive inflows of migrants due to the indirect effect. However, in the rural subsample, these inflows are counteracted by outflows (amounting to two thirds of the inflows), leading to an insignificant overall effect on the net migration rate as seen in the top right plot. This might be because job opportunities are more scarce in rural regions, due to which they are less able to accommodate incoming workers without crowding out present workers into other regions.

Overall, an increase in excess dryness from the median to the 90th percentile implies a decline in the net migration rate of 1.78 percentage points. Thus, around one third of the population decline of 5.7 percent can be explained by the observed migration patterns.

III.D Migrant Selection and Labor Market Outcomes at Destination

III.D.1 Specification

In this section, we turn to the Census micro data in order to document differences in the selection and labor market outcomes of workers that have migrated from another region during the previous five years, depending on whether their origin was affected by dryness. Thus, our aim is to provide descriptive evidence on how outcomes of climate migrants differ from those of "voluntary" migrants and non-migrants in the destination. For this purpose, we use a sample of male workers aged 18 to 64 from the 2010 Census and run the following regression:

$$y_{iod,2010} = \beta_d + \beta_1 Migrant_{iod} + \beta_2 Migrant_{iod} \times Dryness_{io,2001-2010} + \Lambda Age_{iod} + u_{iod}, \tag{7}$$

where o and d are the municipalities of residence in 2005 and in 2010 of individual i, respectively, $Migrant_{iod}$ is a dummy indicating $o \neq d$ and $Dryness_{io,2001-2010}$ is the average number of reported droughts or excess dryness in municipality o between 2001 and 2010. Thus, the base individual in this regression is a non-migrant in municipality of residence d. The vector Age_{iod} includes both age and age squared. As outcomes we consider a dummy indicating whether an individual completed high school, a dummy for being employed and the log of total income.

With the inclusion of destination municipality fixed effects β_d, the interpretation of the coefficients of interest is as follows: β_1 indicates the difference in the outcome between a migrant from a region without droughts or a region with the long-term average SPEI and a worker (of the same age) in the destination municipality, while β_2 indicates how this relative outcome of a migrant differs depending on the dryness in his origin municipality during the decade of the 2000s.

Furthermore, we are also interested in the different selection and relative outcomes of voluntary and climate migrants compared to the population in their *origin*. To capture these differentials, instead of destination fixed effects β_d, we include origin fixed effects β_o (which coincide with β_d for non-migrants) in equation (7). Hence, β_1 and β_2 capture the differences in the outcomes of migrants relative to the population that stayed in the origin municipality.

III.D.2 Results

Table VIII presents the regression results. The first three columns show the estimates with destination fixed effects, while the final three columns show those with origin fixed effects. Note that since around 50 percent of municipalities report zero droughts, the coefficient β_1 in Panel A indicates the average relative outcome of migrants from municipalities in the "less dry" half of the distribution. On the other hand, when using the continuous SPEI in Panel B, β_1 indicates the relative outcome of migrants from municipalities with average weather in terms of dryness.

Looking at the first column of Panel A, we find that migrants from non-drought areas are positively selected in terms of education relative to the destination population. However, the more droughts there are reported in a migrant's origin, the lower is the predicted difference in the probability of having completed high school. While a migrant from a non-drought origin on average has a 4.8 percentage points *higher* probability of being a high school graduate than a non-migrant at the destination, a migrant from a municipality at the 90th percentile of average droughts (0.7 droughts per year) is predicted to have a 7.8 percentage points *lower* probability ($0.0483 - 0.181 \times 0.7$).

Also when using the SPEI in Panel B, we find a significant lower probability of completing high school for migrants from dryer origins. To compare the effects obtained in Panel B with those in Panel A in quantitative terms, we predict first the average relative outcome of migrants from origins in the "less dry" half of the distribution. The average SPEI $\times(-1)$ in this half is -0.438 and thus the predicted average effect for migrants from these origins is $0.00132 + (-0.438 \times -0.0943) = 0.043$. Hence, the difference in the probability of high school graduation for a migrant from an average "wet" origin is very similar to that found in Panel A. Similarly, we can calculate the difference for a migrant who comes from a region at the 90th percentile of the SPEI distribution as $0.00132 + (0.445 \times -0.0943) = -0.041$, which is somewhat smaller effect than the -0.078 found with reported droughts, but still sizable. Hence, we find consistent evidence of climate migrants being negatively selected in terms of education relative to individuals of a similar age in destination regions.

The estimates in column (2) suggest that migrants generally tend to have a higher probability of being employed and that this probability is even higher for migrants from dryer origins. However, climate migrants tend to have a lower total income than other migrants as can be seen in column (3). While migrants from municipalities without droughts earn almost 20 percent more than non-migrants at the destination on average, coming from a municipality at the 90th percentile of droughts implies a 1.73 percent lower income. Similarly, we find in Panel B that coming from a dryer area reduces the relative income.

When inspecting the coefficients of the interaction term in the specification with origin fixed effects, we find that coefficients switch signs in columns (4) and (6). This implies that despite doing worse than other migrants and non-migrants at the destination, those that come from dryer regions have a higher probability of having completed high school and tend to earn more than non-migrants at their *origin*. Especially the income effect is sizable, with a migrant from a region with 0.7 droughts per year earning on average 48 percent more than a non-migrant that stayed in that region.

Thus, our main conclusion from this exercise is that despite having a higher probability of being employed, climate migrants are negatively selected in terms of education relative to other migrants and non-migrants in their destination region and accordingly earn lower incomes. However, migrants from dryer regions tend to have a higher education level and also fare much better in terms of income relative to those that remained in their origin municipality.

III.E Labor Reallocation at Firm-level

III.E.1 Specification

In section III.C, we documented the effect of climate shocks on regions indirectly exposed to such shocks via the formal banking network and the migration network. One potential concern is whether this type of analysis allows to identify the effect of climate shocks on destination economies via labor and capital reallocation. This is because, for example, regions more exposed to droughts at origin via the migration network might also be more connected to those origin regions via other channels, such as trade links. To the extent that trade networks and migrant networks overlap, it is hard to consider the estimated coefficients on the indirect effects documented in section III.C as the sole effect of a specific channel.

To deal with this challenge, we bring our analysis of the effect of climate change on labor reallocation to the firm level. To measure workers' flows across locations and firms we use 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.[10] Workers have unique identifiers that allow us to follow them over time across locations and firms.

We start by constructing a firm-level measure of exposure to past migration from different origins within Brazil. Our approach is similar to the one used to compute the

[10]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).

measures 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:

$$\alpha_{oi(d),t^*} = \frac{L_{i(d),t^*,o\to d}}{L_{i(d),t^*}} \tag{8}$$

Where $\alpha_{oi(d),t^*}$ 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 d, the one where the employer is located in year t^*. When mapping equation (8) to the data, we construct past workers' movements using the period 1998 to 2005, and define our baseline year $t^* = 2005$.[11]

Next, we use the $\alpha_{oi(d)}$ weights to predict future worker flows between origin municipality o and destination firm $i(d)$. 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.

Crucially for our purposes, constructing a measure of exposure to migrant flows at the firm level allows us to exploit variation across firms that operate in the same destination municipality. This allows us to control for any unobservable common shock in the destination labor market, and therefore to identify the effect of climate shocks on destination regions that are solely due to labor reallocation, as follows:

$$\begin{aligned}\frac{L_{oi(d),2006-2010}}{L_{oi(d)}} &= \alpha_o + \alpha_d + \beta_1 \underbrace{\alpha_{oi(d),2005}}_{\text{Exposure to migrants}} \\ &+ \beta_2 \underbrace{\alpha_{oi(d),2005} \times \#droughts_{o,2006-2010}}_{\text{Exposure to droughts via migrants}} + \varepsilon_{oi(d)}\end{aligned} \tag{9}$$

The outcome variable in equation (9) 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 $i(d)$ (where $o \neq d$) between 2006 and 2010, normalized by the total number of workers of firm $i(d)$ observed on average in the same period. This flow can be regressed on a measure of the baseline exposure of firm $i(d)$ to migrants from a given region, and an interaction of such exposure with climate shocks that occurred in the origin between 2006 and 2010. Since the unit of observation is an origin municipality-firm

[11] We also present an alternative specification that focuses on the period 2010-2017. In that specification we construct past workers' movements using the period 1998 to 2010 and define our baseline year $t^* = 2010$.

relationship, we can augment equation (9) with both origin and destination fixed effects.

Estimating equation (9) is computationally intensive as it requires to work with a dataset in which each firm is matched with all the potential origins of migrant workers.[12] Thus, we estimate a simplified version of equation (9) in which we aggregate all potential origin municipalities in two groups: origins with high exposure to climate change shocks during the 2006-2010 period, and those without. We define as origin with high exposure to climate change shocks the municipalities above the 75^{th} percentile of total number of reported droughts, or below the 25^{th} percentile of SPEI-12 (a lower SPEI-12 indicates higher dryness). Regions in the top quartile of the drought distribution experienced, on average, 2.62 more droughts in the five years between 2006 and 2010 than regions in the bottom three quartiles (which on average experienced 0.02 droughts in the same period). Regions in the bottom quartile of SPEI-12 were, on average, 0.76 of a standard deviation drier than those in the rest of the distribution in the same years.

We estimate the following equation:

$$\begin{aligned}\frac{L_{oi(d),2006-2010}}{L_{oi(d)}} &= \alpha_i + 1(\#droughts > p75)_o + \alpha_d + \beta_1 \alpha_{oi(d),2005} \\ &+ \beta_2 \alpha_{oi(d),2005} \times 1(\#droughts > p75)_o + \varepsilon_{oi(d)} \qquad (10)\end{aligned}$$

Since equation (10) uses variation at origin municipality-firm level, it also allows us to control for firm fixed effects (α_i). This specification 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 climate change.[13] In all specifications we cluster standard errors at the destination municipality level to account for spatial correlation of the error terms across firms operating in the same region.

III.E.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 climate change in the 2006-2010 period. In practice, this corresponds to the average of $\alpha_{oi(d),2005} \times 1(\#droughts > p75)_o$ and $\alpha_{oi(d),2005} \times 1(\text{SPEI-12} < p25)_o$ across firms in a given sector or firms in a given size category.

[12] There are about 720,000 firms with at least 5 employees operating in 2005 in the RAIS dataset and 4260 potential origin municipalities.

[13] Since we aggregate origins in two groups, the dummy $1(\#droughts > p75)_o$ in equation (10) effectively captures the origin fixed effect of equation (9).

Figure VIII reports the results by sector. The first finding is that firms in agriculture tend to be more connected to climate change regions via their network of migrant workers. This finding is robust to using droughts (Panel a) or the excess dryness index (Panel b) to capture exposure to climate change. The magnitudes reported in Panel b indicate that the average firm in agriculture has, at baseline, 8 percent of workers coming from regions with excess dryness, about four times more than firms in the manufacturing sector. We get a similar finding when weighting firms by size, as shown in the light gray bars. In particular, among the four main sectors used in our analysis, agriculture and services show the highest connection to areas affected by climate change, while manufacturing and other sectors (a residual category mostly composed by public employees) have the lowest connections, potentially because they are more likely to source their employees locally.

In Figure IX we report the same statistics but splitting firms by size. As shown, differences in the intensity of connections to regions more exposed to climate change are less stark across the firm size distribution. Panel b of Figure VIII, for example, shows that micro, medium and large firms all have about 3 percent of their workers coming from regions with excess dryness.[14]

Next, in Table IX, we report the results of estimating equation (10). The objective of this analysis is to study whether climate change 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 climate change regions also experience larger inflows of workers from those regions. Similarly to the results at municipality level presented in section III.C, Table IX reports results for two definitions of exposure to climate change at origin, one based on reported number of droughts in Panel A, and the second based on the extreme dryness index SPEI-12 in Panel B. In all specifications, we weight observations by firm size.

Let us start by discussing the estimates in Panel A. In column (1), we estimate a version of equation (10) with origin fixed effects, destination municipality fixed effects and our measure of exposure to migrants from a given region as explanatory variables.[15] 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 a firm with a 10 percent higher initial connection to a certain region will increase the flow of workers from that region by about 6 percent of the firm labor force. 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

[14]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.

[15]As explained in the previous section, we aggregate origins in two groups. Thus, the dummy $1(\#droughts > p75)_o$ effectively captures the origin fixed effect.

region and a dummy capturing high exposure to climate change of that origin measured by the number of droughts. The point estimates of both β_1 and β_2 are positive and statistically significant. The estimated coefficient β_2 indicates that workers flows to destination firms are relatively larger from regions that experience a larger increase in droughts during the 2006-2010 period.

Even within a given destination municipality, firms more connected to climate change areas via past migrant flows 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 (10) including firm fixed effects. This specification absorbs any firm-level differences in exposure to climate change areas via other channels, such as trade or capital. 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 climate change areas – such as trade linkages – 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 more exposed to climate change is larger for firms in the agricultural sector than for those in the manufacturing and services sector. In addition, as discussed above and reported in Figure VIII, agricultural firms tend to be on average more connected to affected areas via their past workers' flows. Our estimates indicate that a firm in agriculture with average connection to areas highly affected by droughts experiences a 7 percent larger flow of workers from such regions when the number of droughts at origin increases by 2.62 – the difference between the average number of droughts in the top quartile and the rest of the distribution – in the 2006-2010 period. This effect is about three times larger than the one observed for firms in manufacturing (2.3 percent), while the effect on firms in services is 1.2 percent.

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 to shocks in those regions. In particular, firms with less then 10 employees (micro firms) with average connection to areas highly affected by droughts experience a 3.3 percent larger flow of workers from such regions when the number of droughts at origin increases by 2.62 in the 2006-2010 period. This elasticity is 2.4 percent for medium sized firms, and 1.6 percent for large firms. One reason for this differential increase by firm size is that smaller firms are more likely to use referrals from current employees in their hiring decisions.

Panel B of Table IX estimates a version of equation (10) in which we define as regions with high exposure to climate change the municipalities below the 25^{th} percentile of SPEI-12, where a lower SPEI-12 indicates higher dryness relative to historical average. This measure of dryness only depends on climatic characteristics and it is therefore immune to reporting bias in droughts. Overall, the results are similar, both qualitatively and quantitavely, to those reported in Panel A. In particular, we find larger effects of climate change at origin on worker flows to agricultural firms (2.2 percent) than to manufacturing and service firms (0.7 and 0.8 percent).[16] In terms of firm size, we find that the effect on flows to micro and medium firms (1.3 percent and 1.1 percent respectively) is about twice as large as that to large firms (0.7 percent).

To sum up, the results in Table IX indicate that worker flows to destination firms are relatively larger from regions that experienced a larger number of droughts or higher dryness relative to historical averages. They also indicate that these effects considerably differ in magnitude across firms operating in different sectors and firms of different size. In particular, the estimated elasticities of workers flows are three times larger for firms in the agricultural sector than for firms in the manufacturing sector, and twice as large for small firms than for large 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 – firm characteristics that in the literature have been associated with lower productivity.[17] This implies that climate-driven worker flows are not 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).

Finally, we replicate the analysis of worker flows for the years 2011 to 2017. This analysis uses 2010 as baseline year and measures firm exposure to different origins using flows between 1998 and 2010. The results of this analysis are reported in Table X. Overall, the main results are consistent with those reported in Table IX. However, we find smaller differences in elasticities of worker flows across sectors and across the firm size distribution relative to the previous decade. One potential explanation for these smaller differences is

[16] These quantifications use the logic as for Panel A. For example, the estimate in column (4) of Panel B indicates that a firm in agriculture with average connection to areas highly exposed to excess dryness as captured by SPEI-12 experience a 2.2 percent larger flow of workers from such regions when the dryness is 0.76 of a standard deviation larger at origin in the 2006-2010 period. 0.76 is the difference between average dryness in the bottom quartile and the rest of the distribution.

[17] 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.

that labor market frictions have declined in Brazil relative to the previous decade.

IV Concluding Remarks

We study the effects of climate change on labor and capital reallocation across regions, sectors and firms. In particular, we use a measure of unusual dryness in a location defined as its moisture deficit relative to its 100 year average, which is based on local precipitation and temperature data, the SPEI index. We show that this index is a strong predictor for extreme droughts that occurred in Brazil during the last two decades, as reported to the National System of Civil Protection in Brazil (SINPDEC).

We document two main results. 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 capital outflows, driven by a reduction in loans, consistent with a permanent decrease in investment opportunities. Second, we find that abnormal dryness affects the structure of both the local economy and the economy of areas connected via migrant networks. 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. Regions receiving climate migrants expand employment in agriculture and services, but not in manufacturing. Using social security data, we provide evidence that labor market frictions direct migrants to firms connected to migrants' social networks, which are mostly disconnected from manufacturing firms at destination. This force generates deindustrialization and increases the weight of small firms in the firm size distribution in destination regions.

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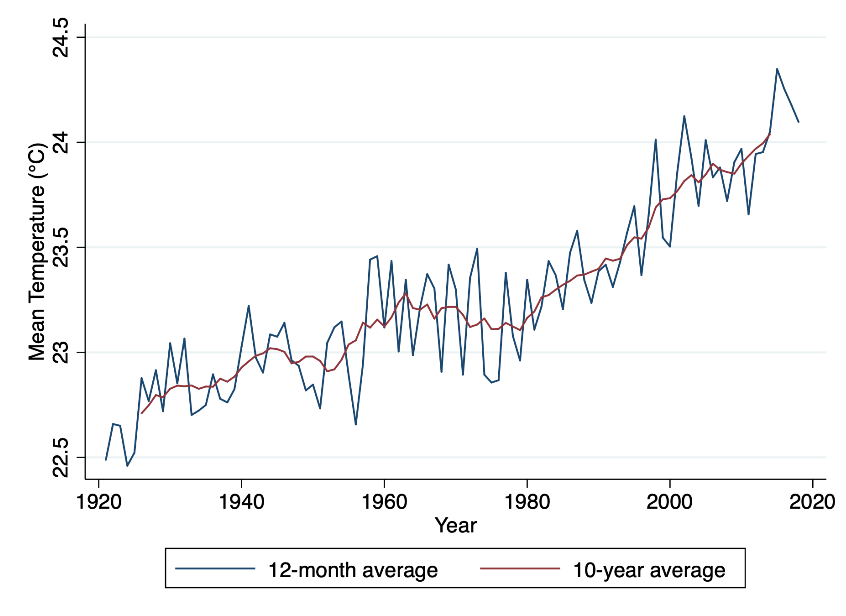
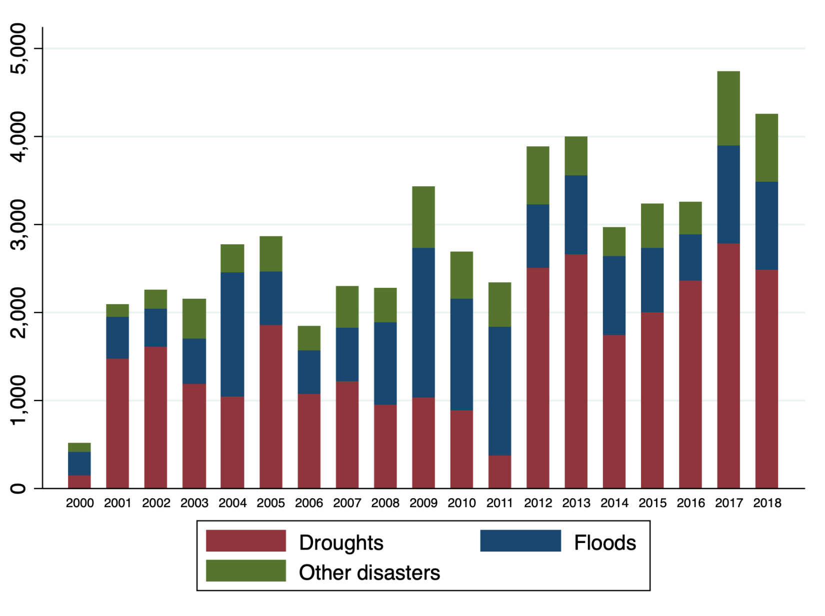
Figures

Figure I: Average temperature in Brazil since 1920



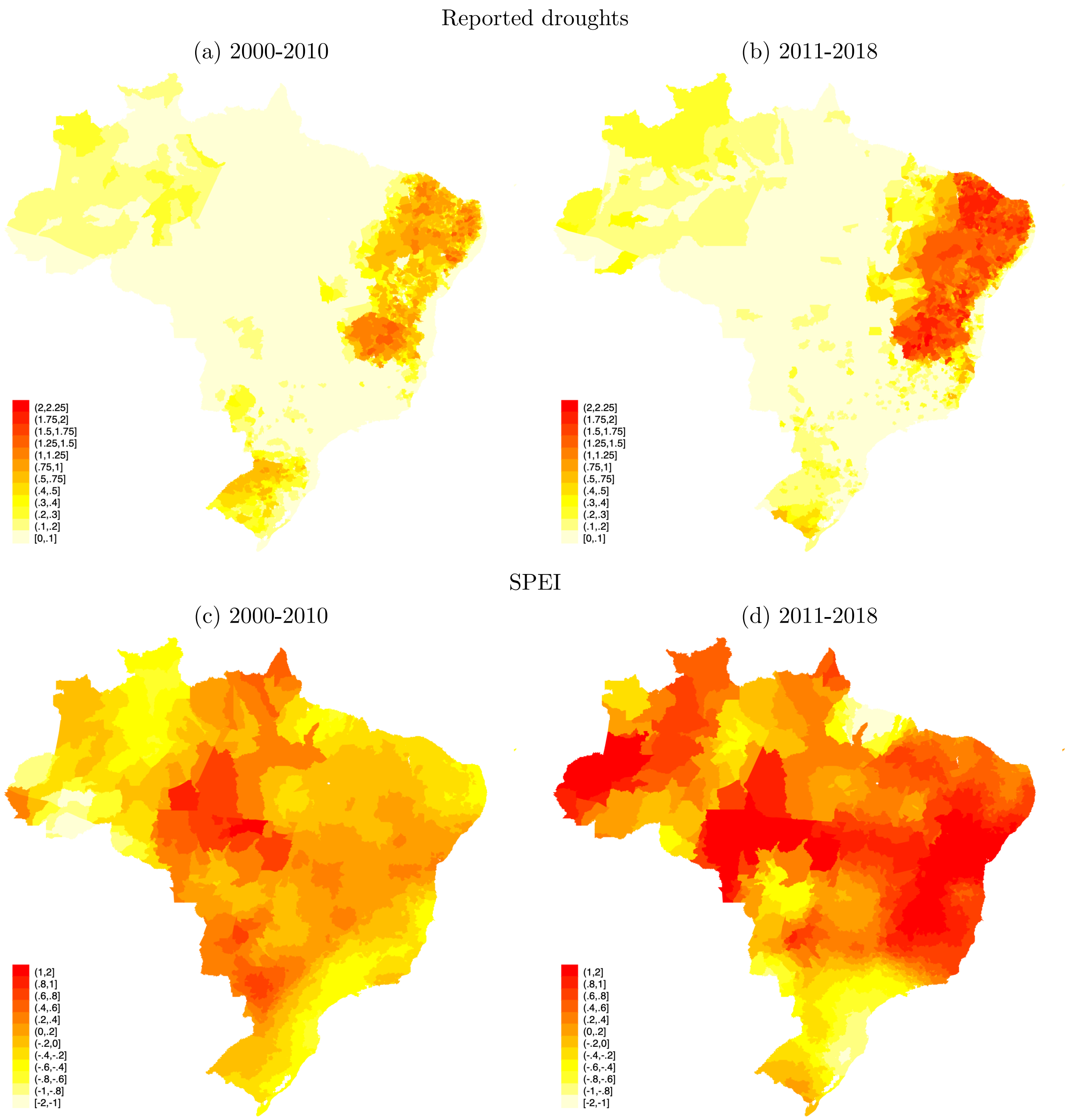
Source: Climatic Research Unit, University of East Anglia, available at `https://lr1.uea.ac.uk/cru/data`.

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



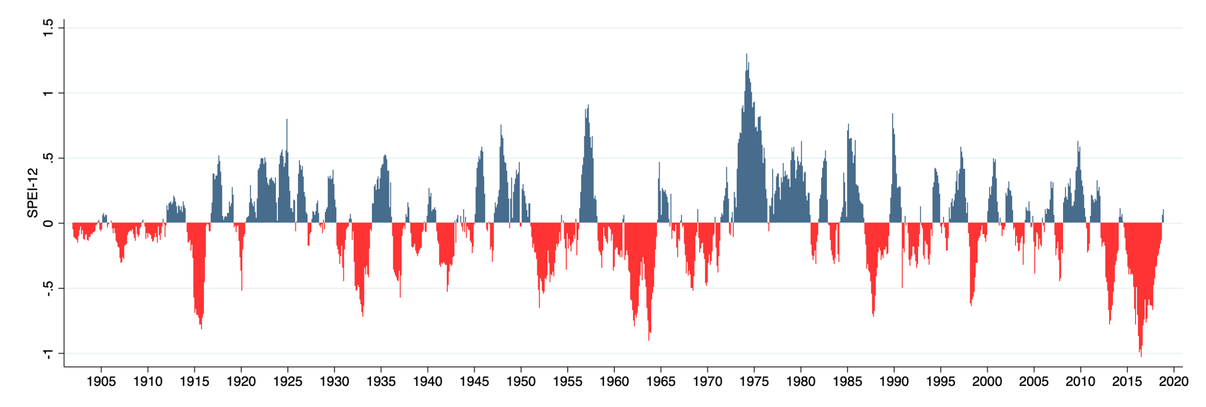
Source: Sistema Nacional de Proteçao e Defesa Civil - SINPDEC

Figure III: Geographical distribution of reported droughts and SPEI



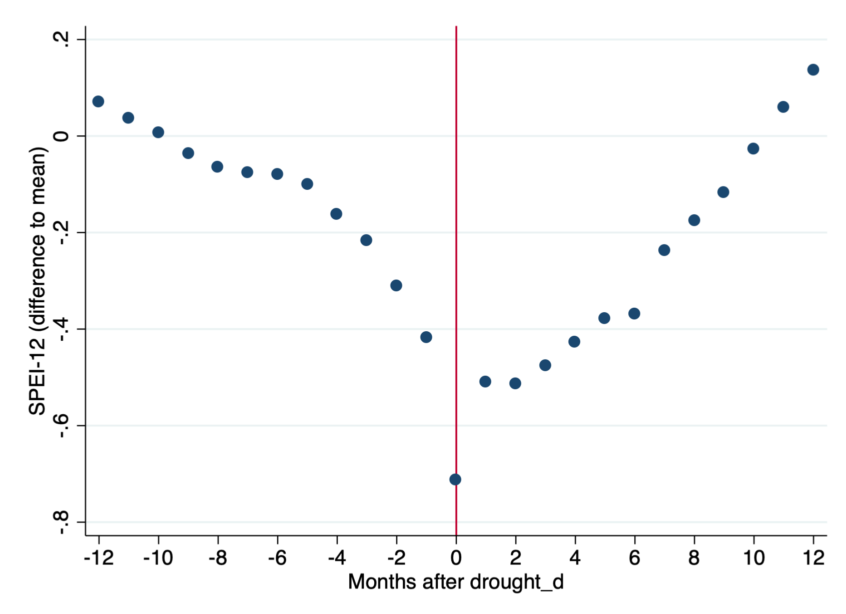
Notes: The upper two maps show the average number of reported droughts per year during the indicated time period. The lower two maps show the average SPEI multiplied by -1 during the indicated time period.

Figure IV: Average monthly SPEI for Brazil since 1902



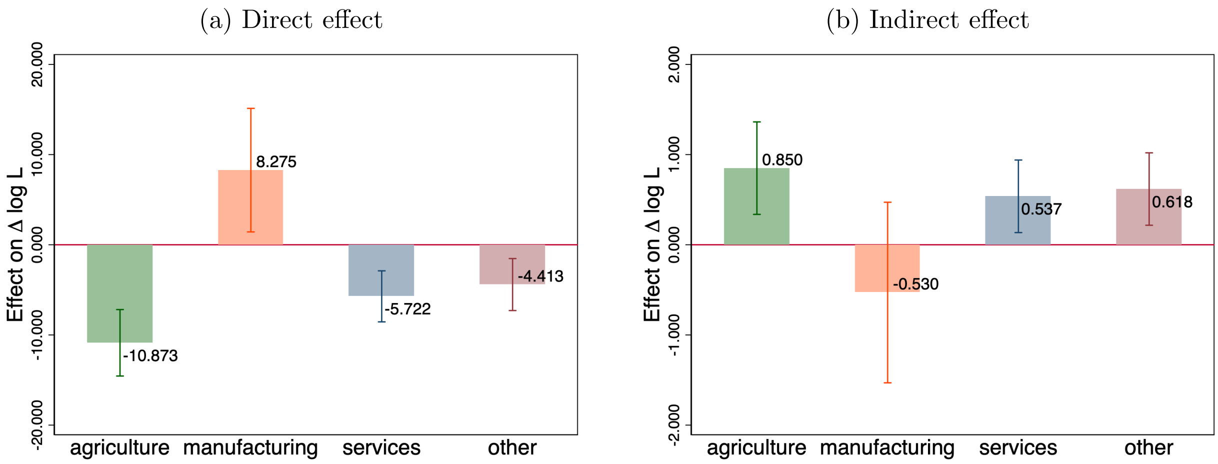
Source: Vicente-Serrano et al. (2010), available at `https://spei.csic.es/database.html`

Figure V: SPEI around drought events



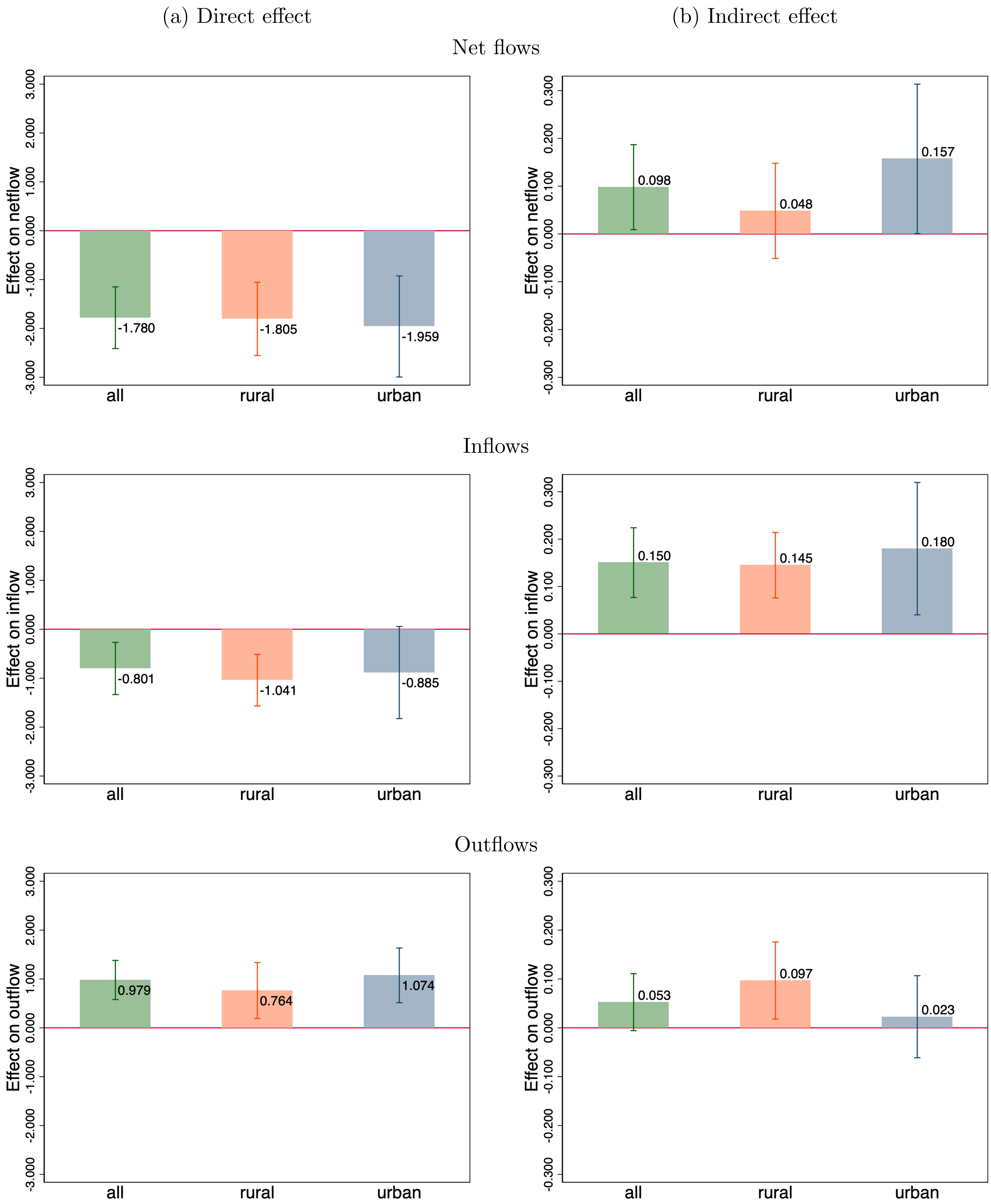
Notes: The figures shows the coefficients of a regression of the SPEI on a constant and 12 leads and 12 lags of a dummy indicating a reported drought, using monthly data at the municipality level from 2000 to 2018.

Figure VI: Effects of SPEI on Change in Employment



Notes: The plot on the left shows the percentage change in employment predicted in a municipality moving from the median to the 90th percentile of the distribution of the average SPEI$\times(-1)$ during 2001-2010, which implies an increase by 0.44. The plot on the right shows the effect when 10% of the origins of migrants received during 1995-2000 move from the median to the 90th percentile of the distribution of the average SPEI$\times(-1)$. The predictions are based on the estimates in Panel B of Table VI.

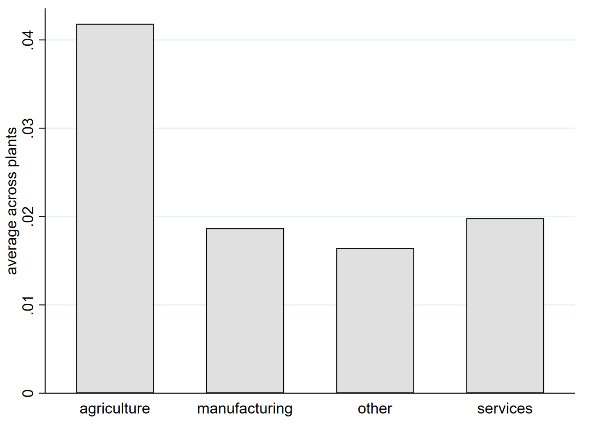
Figure VII: Effects of SPEI on Migration Flows



Notes: The plots on the left show the percentage point change in the 2005-2010 net-, in- or out-migration rate of a municipality moving from the median to the 90th percentile of the distribution of the average SPEI$\times(-1)$ during 2001-2010, which implies an increase by 0.44. The plots on the right show the effects when 10% of the origins of migrants received during 1995-2000 move from the median to the 90th percentile of the distribution of the average SPEI$\times(-1)$. The predictions are based on the estimates in Panel B of Table VII.

Figure VIII: Firm Exposure to Climate Shocks via Past Workers' Flows - by Sector

(a) Initial connections to drought areas



(b) Initial connections to dry areas

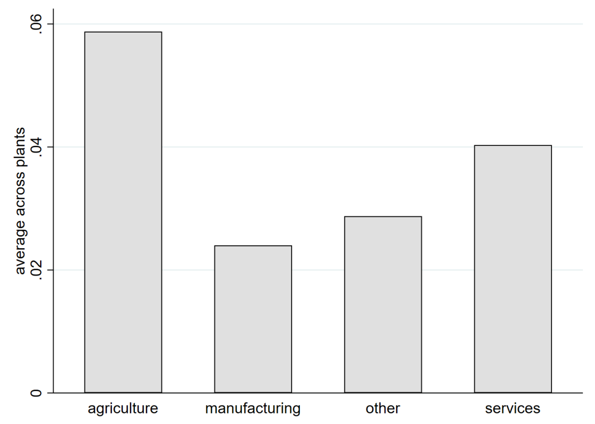
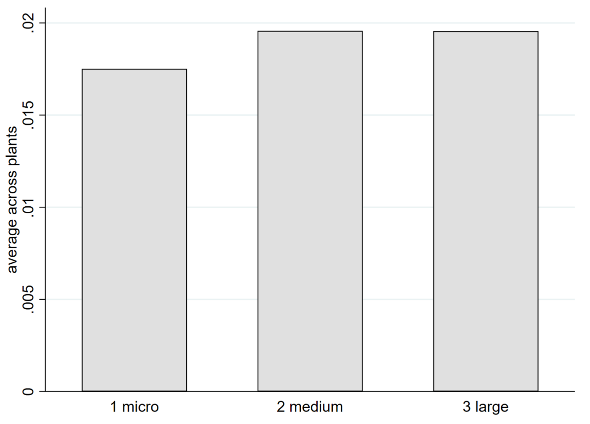
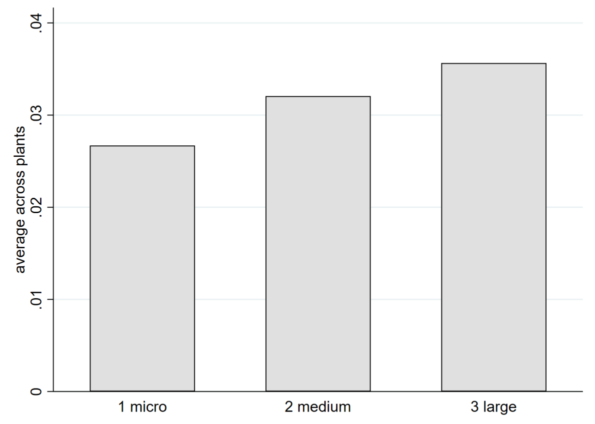


Figure IX: Firm Exposure to Climate Shocks via Past Workers' Flows - by Size

(a) Initial connections to drought areas



(b) Initial connections to dry areas



Tables

Table I: Number of reported droughts and excess dryness index (SPEI-12), 2000-2010

VARIABLES	(1) # droughts	(2) 1(drought> 0)	(3) # droughts	(4) # droughts	(5) # droughts
SPEI-12	-0.0703***	-0.0601***			
	(0.00311)	(0.00251)			
# months with SPEI-12<=-1			0.0126***		
			(0.000844)		
# months with SPEI-12<=-1.5				0.0137***	
				(0.00123)	
# months with SPEI-12<=-2					0.0233***
					(0.00209)
Observations	46,794	46,794	46,794	46,794	46,794
R-squared	0.495	0.529	0.492	0.490	0.490
Year and AMC FE	y	y	y	y	y
RuralShare1991 x year FE	y	y	y	y	y
Dist Coast x year FE	y	y	y	y	y
Macro-region x year FE	y	y	y	y	y
First Stage F-stat	513	578	224	124	124

Notes: First stage F-stat is the Kleibergen-Paap rk Wald F statistic. Standard errors are clustered at the AMC level. A control for the number of reported floods is included in all columns.

Table II: Effects of droughts on agricultural outcomes

Panel A: Reported droughts

VARIABLES	(1) log area planted 2000-2010	(2) log area harvested 2000-2010	(3) log value production 2000-2010	(4) log area planted 2011-2018	(5) log area harvested 2011-2018	(6) log value production 2011-2018
# Droughts	0.000702	-0.0411***	-0.0923***	-0.0593***	-0.0879***	-0.135***
	(0.00460)	(0.00597)	(0.00714)	(0.00637)	(0.00821)	(0.00917)
Observations	46,228	46,224	46,224	33,599	33,549	33,548
R-squared	0.960	0.949	0.943	0.952	0.937	0.943
Year and AMC FE	y	y	y	y	y	y
RuralShare1991 x year FE	y	y	y	y	y	y
Dist Coast x year FE	y	y	y	y	y	y

Panel B: Excess dryness index

VARIABLES	(1) log area planted 2000-2010	(2) log area harvested 2000-2010	(3) log value production 2000-2010	(4) log area planted 2011-2018	(5) log area harvested 2011-2018	(6) log value production 2011-2018
SPEI-12 $\times$(-1)	-0.0158***	-0.0274***	-0.0524***	-0.0467***	-0.0699***	-0.0741***
	(0.00294)	(0.00321)	(0.00380)	(0.00304)	(0.00354)	(0.00358)
Observations	46,228	46,224	46,224	33,599	33,549	33,548
R-squared	0.960	0.949	0.943	0.952	0.937	0.943
Year and AMC FE	y	y	y	y	y	y
RuralShare1991 x year FE	y	y	y	y	y	y
Dist Coast x year FE	y	y	y	y	y	y

Notes: Standard errors are clustered at the AMC level. A control for the number of reported floods is included in all columns. Data are at the yearly level and range from 2000 to 2010.

Table III: Direct and Indirect effects on capital outcomes, yearly 2000-2010

Panel A: Reported droughts

VARIABLES	(1) log deposits	(2) log loans	(3) K outflows	(4) K outflows
# Droughts	-0.0124***	-0.0168**	-0.00275	-0.00539
	(0.00388)	(0.00694)	(0.00426)	(0.00436)
Indirect exposure to droughts via bank networks				0.355***
				(0.109)
Observations	33,380	33,380	33,380	33,380
R-squared	0.984	0.970	0.813	0.813
Year and AMC FE	y	y	y	y
Rural91 x year FE	y	y	y	y
DistCoast x year FE	y	y	y	y
Macro x year FE	y	y	y	y

Panel B: Excess dryness index

VARIABLES	(1) log deposits	(2) log loans	(3) K outflows	(4) K outflows
SPEI-12 $\times(-1)$	-0.00541*	0.0148***	-0.0161***	-0.0178***
	(0.00281)	(0.00470)	(0.00284)	(0.00294)
Indirect exposure to SPEI-12 $\times(-1)$ via bank networks				0.0465**
				(0.0235)
Observations	33,380	33,380	33,380	33,380
R-squared	0.984	0.970	0.814	0.814
Year and AMC FE	y	y	y	y
Rural91 x year FE	y	y	y	y
DistCoast x year FE	y	y	y	y
Macro x year FE	y	y	y	y

Notes: Standard errors are clustered at the municipality level. A control for the number of reported floods is included in all columns.

Table IV: Capital outcomes, decadal changes 2000-2010

Panel A: Reported droughts

VARIABLES	(1) Δ log deposits	(2) Δ log loans	(3) K outflows
# Droughts	-0.0441	0.0165	-0.0817**
	(0.0403)	(0.0681)	(0.0367)
Indirect exposure to droughts via bank networks			0.114
			(0.0736)
Observations	2,799	2,799	2,795
R-squared	0.168	0.146	0.060
Macro FE	y	y	y
Controls	y	y	y

Panel B: Excess dryness index

VARIABLES	(1) Δ log deposits	(2) Δ log loans	(3) K outflows
SPEI-12 $\times(-1)$	-0.0534	-0.295***	0.0530*
	(0.0360)	(0.0580)	(0.0314)
Indirect exposure to SPEI-12 $\times(-1)$ via bank networks			2.228***
			(0.347)
Observations	2,799	2,799	2,795
R-squared	0.168	0.155	0.081
Macro FE	y	y	y
Controls	y	y	y

Notes: Robust standard errors are reported in parenthesis. The set of additional controls at the municipality level includes 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: Change in Population: 2000-2010

Panel A: Reported droughts

VARIABLES	(1) Δ log Pop all	(2) all	(3) all	(4) rural	(5) urban
# Droughts	-0.0401***	-0.0135*	-0.0391***	-0.0171	-0.0688***
	(0.00629)	(0.00698)	(0.0110)	(0.0140)	(0.0176)
Indirect exposure to droughts			0.0599***	0.0148	0.156***
			(0.0194)	(0.0243)	(0.0325)
Observations	4,254	4,249	4,248	2,126	2,122
R-squared	0.110	0.176	0.178	0.220	0.147
mean Y	.159	.159	.159	.145	.173
Macro-region FE	y	y	y	y	y
Controls	n	y	y	y	y

Panel B: Excess dryness index

VARIABLES	(1) Δ log Pop all	(2) all	(3) all	(4) rural	(5) urban
SPEI-12 $\times(-1)$	-0.0645***	-0.0595***	-0.130***	-0.119***	-0.144***
	(0.00683)	(0.00701)	(0.0185)	(0.0282)	(0.0240)
Indirect exposure to SPEI-12 $\times(-1)$			0.113***	0.0731**	0.151***
			(0.0253)	(0.0365)	(0.0344)
Observations	4,254	4,249	4,248	2,126	2,122
R-squared	0.122	0.190	0.194	0.238	0.159
mean Y	.159	.159	.159	.145	.173
Macro-region FE	y	y	y	y	y
Controls	n	y	y	y	y

Notes: Robust standard errors are reported in parenthesis. The set of additional controls at the municipality level includes 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: Change in Employment: 2000-2010

Panel A: Reported droughts

VARIABLES	(1) Δ log L all	(2) agriculture	(3) manufacturing	(4) services	(5) other
# Droughts	-0.0414**	-0.0664**	0.0286	-0.0420*	-0.0569**
	(0.0164)	(0.0273)	(0.0533)	(0.0226)	(0.0230)
Indirect exposure to droughts	0.100***	0.188***	-0.0466	0.190***	0.0649
	(0.0294)	(0.0500)	(0.0985)	(0.0405)	(0.0424)
Observations	4,248	4,248	4,241	4,248	4,248
R-squared	0.128	0.058	0.080	0.082	0.043
mean Y	.185	.003	.247	.293	.302
Macro-region FE	y	y	y	y	y
Controls	y	y	y	y	y

Panel B: Excess dryness index

VARIABLES	(1) Δ log L all	(2) agriculture	(3) manufacturing	(4) services	(5) other
SPEI-12 $\times(-1)$	-0.0885***	-0.247***	0.188**	-0.130***	-0.100***
	(0.0236)	(0.0427)	(0.0794)	(0.0328)	(0.0334)
Indirect exposure to SPEI-12 $\times(-1)$	0.0894***	0.193***	-0.120	0.122***	0.140***
	(0.0334)	(0.0594)	(0.116)	(0.0466)	(0.0466)
Observations	4,248	4,248	4,241	4,248	4,248
R-squared	0.130	0.070	0.083	0.080	0.044
mean Y	.185	.003	.247	.293	.302
Macro-region FE	y	y	y	y	y
Controls	y	y	y	y	y

Notes: Robust standard errors are reported in parenthesis. The set of additional controls at the municipality level includes 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 VII: Migration Flows between 2005-2010

Panel A: Reported droughts

VARIABLES	(1) Net all	(2) In all	(3) Out all	(4) Net rural	(5) Net urban
# Droughts	-0.0253***	-0.0226***	0.00274	-0.0123**	-0.0406***
	(0.00420)	(0.00288)	(0.00307)	(0.00502)	(0.00747)
Indirect exposure to droughts	0.0186**	0.0125**	-0.00612	0.0210**	0.0284**
	(0.00792)	(0.00571)	(0.00582)	(0.00976)	(0.0139)
Observations	4,248	4,248	4,248	2,128	2,120
R-squared	0.212	0.290	0.166	0.210	0.148
Macro-region FE	y	y	y	y	y
Controls	y	y	y	y	y

Panel B: Excess dryness index

VARIABLES	(1) Net all	(2) In all	(3) Out all	(4) Net rural	(5) Net urban
SPEI-12 $\times(-1)$	-0.0405***	-0.0182***	0.0222***	-0.0410***	-0.0445***
	(0.00731)	(0.00618)	(0.00464)	(0.00868)	(0.0120)
Indirect exposure to SPEI-12 $\times(-1)$	0.0223**	0.0342***	0.0119*	0.0110	0.0357**
	(0.0103)	(0.00854)	(0.00676)	(0.0115)	(0.0181)
Observations	4,248	4,248	4,248	2,128	2,120
R-squared	0.221	0.285	0.207	0.234	0.150
Macro-region FE	y	y	y	y	y
Controls	y	y	y	y	y

Notes: Robust standard errors are reported in parenthesis. The set of additional controls at the municipality level includes 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 VIII: Individual level regressions

Panel A: Reported droughts

VARIABLES	(1) HS grad	(2) Empl	(3) log Income	(4) HS grad	(5) Empl	(6) log Income
Migrant	0.0483***	0.0119***	0.193***	0.0234***	0.0168***	0.192***
	(0.00278)	(0.00261)	(0.00865)	(0.00776)	(0.00342)	(0.0227)
Migrant × # Droughts	-0.181***	0.0689***	-0.274***	0.0257**	0.182***	0.418***
	(0.0211)	(0.00477)	(0.0379)	(0.0118)	(0.00981)	(0.0167)
Observations	5,243,677	6,273,292	4,607,486	5,243,677	6,273,292	4,607,486
R-squared	0.095	0.103	0.255	0.095	0.099	0.249
Fixed effects	destin.	destin.	destin.	origin	origin	origin

Panel B: Excess dryness index

VARIABLES	(1) HS grad	(2) Empl	(3) log Income	(4) HS grad	(5) Empl	(6) log Income
Migrant	0.00132	0.0307***	0.123***	0.0292***	0.0591***	0.289***
	(0.00601)	(0.00250)	(0.00910)	(0.00655)	(0.00435)	(0.0226)
Migrant × SPEI-12 $\times(-1)$	-0.0943***	0.0397***	-0.139***	0.0101	0.0754***	0.178***
	(0.0126)	(0.00445)	(0.0261)	(0.0105)	(0.00640)	(0.0189)
Observations	5,243,677	6,273,292	4,607,486	5,243,677	6,273,292	4,607,486
R-squared	0.094	0.103	0.254	0.095	0.098	0.248
Fixed effects	destin.	destin.	destin.	origin	origin	origin

Notes: Data come from the Brazilian Census 2010 and include male individuals aged 18-64. *Migrant* is an indicator for having resided in a different municipality in 2005. *Droughts* and *SPEI-12*$\times(-1)$ refer to the origin municipality of migrants. Standard errors clustered at destination municipality are reported in parenthesis.

Table IX: Workers' Flows to Firms Exposed to Climate Change, 2006-2010

Panel A: Reported droughts

VARIABLES	(1) $\frac{L_{oi(d)2006-2010}}{Lavg_i}$ all	(2) all	(3) all	(4) agri	(5) manuf	(6) services	(7) micro	(8) medium	(9) large
firm connection to origin × 1(#droughts> p75)		0.257***	0.388***	0.638***	0.466***	0.226***	0.714***	0.463***	0.315***
		(0.0395)	(0.0527)	(0.0763)	(0.0781)	(0.0686)	(0.0297)	(0.0307)	(0.0646)
firm connection to origin	0.642***	0.397***	0.462***	0.476***	0.406***	0.446***	0.319***	0.418***	0.492***
	(0.0149)	(0.0154)	(0.0144)	(0.0449)	(0.0210)	(0.0171)	(0.00981)	(0.0101)	(0.0177)
Observations	1,415,758	1,415,758	1,415,758	67,756	248,742	983,990	477,882	711,412	223,762
R-squared	0.267	0.393	0.683	0.649	0.673	0.708	0.627	0.647	0.696
mean Y	.13	.13	.13	.13	.13	.13	.13	.13	.13
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

Panel B: Excess dryness index

VARIABLES	(1) $\frac{L_{oi(d)2006-2010}}{Lavg_i}$ all	(2) all	(3) all	(4) agri	(5) manuf	(6) services	(7) micro	(8) medium	(9) large
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)
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
mean Y	.13	.13	.13	.13	.13	.13	.13	.13	.13
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.

Table X: Workers' Flows to Firms Exposed to Climate Change, 2011-2017

Panel A: Reported droughts

VARIABLES	(1) $\frac{L_{oi(d)2006-2010}}{Lavg_i}$ all	(2) all	(3) all	(4) agri	(5) manuf	(6) services	(7) micro	(8) medium	(9) large
firm connection to origin × 1(#droughts> p75)		0.423***	0.754***	0.746***	0.877***	0.546***	0.928***	0.697***	0.666***
		(0.0772)	(0.120)	(0.0711)	(0.0965)	(0.0828)	(0.0359)	(0.0397)	(0.142)
firm connection to origin	0.756***	0.414***	0.489***	0.482***	0.401***	0.507***	0.341***	0.482***	0.530***
	(0.0117)	(0.0139)	(0.0156)	(0.0440)	(0.0187)	(0.0196)	(0.00957)	(0.0142)	(0.0198)
Observations	2,265,438	2,265,438	2,265,438	103,258	331,586	1,654,030	863,664	1,106,858	290,524
R-squared	0.295	0.432	0.699	0.695	0.701	0.719	0.676	0.673	0.710
mean Y	.158	.158	.158	.158	.158	.158	.158	.158	.158
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

Panel B: Excess dryness index

VARIABLES	(1) $\frac{L_{oi(d)2006-2010}}{Lavg_i}$ all	(2) all	(3) all	(4) agri	(5) manuf	(6) services	(7) micro	(8) medium	(9) large
firm connection to origin × 1(SPEI-12 < p25)		0.305***	0.474***	0.522***	0.610***	0.481***	0.684***	0.552***	0.399***
		(0.0340)	(0.0426)	(0.0853)	(0.0645)	(0.0486)	(0.0508)	(0.0462)	(0.0458)
firm connection to origin	0.712***	0.480***	0.592***	0.636***	0.456***	0.617***	0.489***	0.610***	0.620***
	(0.0110)	(0.0177)	(0.0275)	(0.0464)	(0.0186)	(0.0378)	(0.0253)	(0.0250)	(0.0297)
Observations	2,265,438	2,265,438	2,265,438	103,258	331,586	1,654,030	863,902	1,106,626	290,564
R-squared	0.276	0.358	0.663	0.641	0.674	0.666	0.548	0.607	0.689
mean Y	.158	.158	.158	.158	.158	.158	.158	.158	.158
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.