The Effects of Climate Change on Labor Reallocation

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Abstract

Climate change is expected to reduce agricultural productivity in developing countries. Classic international trade and geography models predict that the optimal adaptation response is a reallocation of labor from agriculture towards other sectors gaining comparative advantage. In this paper, we provide evidence on the effects of recent changes in climate in Brazil on this reallocation process. We document that persistent increases in dryness generate a large reduction in agricultural employment. Workers staying in drying regions reallocate towards manufacturing but climate migrants are allocated to small firms outside of manufacturing in destination regions. This asymmetry suggests that spatial labor market frictions constrain the reallocation process from agriculture to manufacturing. We propose a direct measure of spatial labor market frictions using social security data that confirms that firms in the industrial sector are less integrated to labor markets in areas suffering droughts.

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I Introduction

Climate change is expected to generate persistent declines in agricultural productivity in many developing countries, particularly those located in tropical and subtropical regions (IPCC 2021). Understanding how economies adjust to these shocks is central to assessing the long-run costs of climate change. Classic trade and spatial equilibrium models predict that declining agricultural productivity should trigger a reallocation of labor and capital away from agriculture and toward sectors and regions with higher returns.[1] In practice, however, this adjustment process may be constrained by frictions in labor and capital markets, limiting economies' ability to adapt efficiently.

In Mestieri et al. (2025), we study how climate-induced productivity shocks propagate across space through labor migration and bank branch networks. That paper develops a quantitative spatial equilibrium framework and shows that persistent increases in excess dryness in Brazil generate sharp contractions in credit not only in directly affected regions but also in financially integrated regions. While the banking system provides insurance against short-run weather shocks, persistent droughts lead to a disruption of credit supply that propagates through bank networks, constraining capital reallocation across space. In parallel, climate shocks induce large migration flows along pre-existing migrant networks, reshaping local labor markets.

This paper builds on Mestieri et al. (2025) by studying how these spatial labor and capital flows translate into sectoral reallocation *within* and *across* regions. While our previous work focuses on aggregate employment, migration, and credit, the present paper asks a more granular question: how do climate shocks reshape the allocation of labor and capital across agriculture, manufacturing, and services, both locally and in regions connected through factor markets? Answering this question is essential for understanding whether climate change accelerates or hinders structural transformation, and whether factor market frictions distort the sectoral allocation of resources.

We address this question by combining a simple small-open-economy framework extending the classic Ricardo-Viner model[2] with detailed data on sectoral employment, migration, and credit flows across Brazilian municipalities. We show that persistent increases in excess dryness generate a large contraction in lending to both agricultural and non-agricultural firms, not only in directly affected municipalities but also in financially integrated regions. Consistent with this contraction in credit, manufacturing employment falls sharply in regions exposed to climate shocks through bank branch networks. Turning to labor markets, we find that regions directly affected by excess dryness experience large employment declines in the agricultural and service sectors, while local manufacturing absorbs only a fraction of displaced workers and most adjustment occurs through

[1] Corden and Neary (1982); Matsuyama (1992); Krugman (1991).

[2] For a textbook discussion, refer to Dixit and Norman (1980).

out-migration, with climate migrants disproportionately allocated to agriculture and services rather than manufacturing in destination regions. Together, these findings indicate that while climate change triggers substantial reallocation of labor and capital, spatial labor market frictions and financial constraints severely limit the ability of manufacturing to absorb displaced factors, distorting the adjustment process predicted by frictionless models.

In the neoclassical framework guiding our empirical analysis, factor allocation across the two tradable sectors – agriculture and manufacturing – depends on comparative advantage, which is driven both by relative productivity and factor abundance. In turn, the employment share of the non-tradable service sector depends on local demand, which is a function of local income per capita. A local increase in dryness reduces agricultural productivity, which worsens comparative advantage of local agriculture relative to local manufacturing. In addition, it reduces land rents and the local demand for services. Thus, labor and capital reallocate away from both agriculture and services into local manufacturing.

The model also generates predictions for the *indirect effects* of excess dryness in regions integrated with areas suffering droughts through goods, labor or capital markets. First, because all regions are price takers in international markets, there are no spillover effects through goods markets. Still, the model generates predictions for the effects through labor and capital markets in regions which are the destination of factor inflows from other regions. We think of these inflows as permanent changes in the supply of labor or capital that are exogenous from the point of view of the destination region. An inflow of mobile production factors increases the scarcity of the fixed factor land and thus reduces the comparative advantage of the agricultural sector. In addition, a higher scarcity of land implies lower relative income in traded goods and a lower relative demand for services. As a result, the indirect effect of dryness through labor or capital inflows is an increase in the manufacturing employment share of both factors.

We confront these predictions with rich administrative and census data from Brazil, which allow us to track both sectoral outcomes and spatial factor flows. As in Mestieri et al. (2025), we combine municipality-level Population Census data with detailed information on bank branch balance sheets from the Central Bank of Brazil (ESTBAN). The Census data allow us to measure employment, sectoral composition, and migration flows across municipalities over time, covering both formal and informal workers. The bank branch data provide a comprehensive picture of credit allocation across regions and sectors, and allow us to construct measures of financial integration based on the structure of banks' branch networks.

A novel contribution of this paper is the use of matched employer–employee data from the Brazilian Annual Social Information System (RAIS) to study the microeconomic mechanisms underlying spatial labor reallocation. RAIS covers the universe of formal employment relationships in Brazil and allows us to track workers across firms, sectors, and municipalities over time. Relative to Census data, RAIS offers three key advantages. First, it provides firm-level identifiers, which allow us to observe directly how migrant workers are allocated across firms within the same destination labor market, rather than only across sectors or municipalities. Second, it contains detailed employment histories that make it possible to construct firm-specific measures of exposure to migrant networks based on past worker flows, which we interpret as revealing spatial labor market frictions in hiring and matching. Third, the panel structure of RAIS allows us to control flexibly for firm fixed effects, isolating within-firm responses to climate-driven labor supply shocks. These features enable us to directly test whether manufacturing firms face systematically higher barriers to absorbing climate migrants than firms in other sectors.

Our empirical analysis yields four main findings. First, we document that persistent increases in excess dryness generate a large contraction in lending to both agricultural and non agricultural firms. This contraction operates both directly, in municipalities experiencing higher excess dryness, and indirectly, in municipalities financially integrated with affected areas through bank branch networks. In contrast, municipalities exposed to excess dryness through migration links experience an increase in lending, which is stronger outside the agricultural sector. This pattern is consistent with the model prediction that an inflow of labor into a region leads to a relatively stronger expansion of the local manufacturing sector.

Second, turning to the sectoral allocation of labor, we find that, consistent with the neoclassical benchmark, regions directly affected by persistent increases in excess dryness experience a sharp contraction in agricultural employment and a decline in service sector employment. While this leads to spatial reallocation of workers through out-migration and an overall employment decline, as extensively studied in Mestieri et al. (2025), we find that local manufacturing expands by absorbing a part of the displaced workforce, indicating that within-region sectoral reallocation broadly follows the efficient adjustment path predicted by the model.

Third, regions financially connected to those hit by dryness experience a sharp decline in manufacturing employment. This result is consistent with the fall in lending we observe in such regions and the model prediction that a fall in overall capital implies a reallocation of labor out of manufacturing and into the remaining sectors.

Fourth, spatial reallocation of labor across regions is severely distorted by factor market frictions. Migrants from drought-affected regions are less likely to reallocate into the manufacturing than other sectors in destination municipalities, which is inconsistent with the model prediction that manufacturing should expand when labor inflows increase. Instead, climate migrants are disproportionately absorbed by agriculture and services. These patterns stand in contrast to frictionless models, which predict that manufacturing should expand in regions receiving labor.

To shed more light on the mechanisms behind these discrepancies, we exploit matched employer-employee data to measure spatial labor market frictions at the firm level. We show that manufacturing firms are significantly less connected to migrant networks than firms in agriculture or services, largely because manufacturing is geographically concentrated and relies more heavily on local labor markets. As a result, displaced agricultural workers face higher matching frictions when attempting to enter manufacturing jobs outside their origin regions and are more likely to find jobs in smaller firms outside manufacturing. Once we account for these asymmetric spatial frictions, the observed sectoral allocation of migrants aligns closely with the model's predictions.

An alternative explanation for this lack of spatial labor reallocation into manufacturing is that workers displaced by drier climatic conditions – and especially former agricultural workers – might not have the skills required to work in manufacturing in destination regions. In this case, the absence of migrant reallocation into manufacturing would not reflect spatial frictions but an optimal allocation of labor at destination. To investigate this mechanism, we split workers by their level of education. We find that low-skill workers are more likely to relocate into the agricultural sector, while high-skill workers are more likely to relocate into services. However, neither low-skill nor high-skill workers relocate into manufacturing, which suggests that labor market frictions play a role.

Our findings imply that spatial capital and labor market frictions are a major constraint to factor reallocation in response to climate change. The optimal response to lower agricultural productivity would be a reallocation of both factors towards the other traded sector, manufacturing, which is concentrated in space. As a result, a large part of this reallocation process needs to take place across regions. However, we find that spatial capital and labor market frictions constrain spatial factor reallocation towards manufacturing. This limits the ability of developing economies to use migration and capital flows to facilitate structural transformation in response to climate change. Our results thus underscore the importance of policies that ease inter regional labor matching and improve the resilience of financial intermediation. Without such policies, climate change may not only reduce agricultural productivity but also slow structural transformation by misallocating labor and capital across space and sectors.

Related Literature

We contribute to the literature studying adaptation to climate change in developing countries. A key channel of adjustment highlighted by quantitative spatial models is factor reallocation from the directly affected rural agricultural sector to the industrial and service sectors in distant urban regions (Conte et al. 2021). However, there is scarce direct empirical evidence on the effects of climate change on factor reallocation across sectors and regions.

With respect to labor reallocation, a few recent empirical studies focus on the effects of climate change on urbanization and structural transformation. Henderson et al. (2017) show that long-term increases in dryness in sub-saharan Africa only had positive effects on urbanization in regions where cities are likely to be manufacturing centers. They interpret their findings in light of a small open economy model where agricultural labor can only reallocate towards traded manufacturing given the reduction in demand for services. Our findings for the local effects of droughts in Brazil are in line with their interpretation while our findings for the indirect effects point in a different direction as a large part of the adjustment takes place through out-migration flows and migrants are less likely to find jobs in manufacturing than other sectors in destination regions. This is because, even in the presence of manufacturing firms at destination, asymmetric spatial labor market frictions direct migrants towards jobs in agriculture or services.

Recent empirical studies in India by Emerick (2018), Santangelo (2019) and Colmer (2021) show that short-run weather shocks induce local labor reallocation across sectors but do not induce migration. In turn, contemporaneous work by Liu et al. (2023) shows that long-term increases in temperature in India generate an increase in the local agricultural employment share and no out-migration. Our findings for the local effects of persistent droughts in Brazil have the opposite sign: a reduction in the local agricultural employment share and large out-migration flows. This difference in findings for India and Brazil is informative about the relevant margins of adjustment to climate change for countries with different levels of internal market integration. The findings for India can be rationalized by a model with large spatial frictions in both goods and labor markets.[3] In this case, Nath (2022) shows that if agriculture is a subsistence good, then the reduction in local agricultural income can increase employment in local agriculture. In contrast, in Brazil, agricultural and manufacturing goods are traded, with limited subsistence agricultural activities. Thus, a reduction in local agricultural productivity leads to labor reallocation towards local manufacturing. Similarly, regional labor markets are more integrated than in India so that large part of the adjustment takes place through out-migration.[4]

Finally, our paper is related to the recent literature developing quantitative trade and spatial models to estimate the effects of future changes in climate on the spatial allocation

[3] The role of internal trade frictions in India has been explored by Burgess and Donaldson (2010) who find that local rainfall shortages were less likely to cause famines in colonial India after railroad access increased trade openness. More recently, Allen and Atkin (2022) show that expansions of the Indian highway network reduced the responsiveness of local prices to local rainfall but increased the responsiveness of local prices to yields elsewhere so that farmers shifted their production towards crops with less volatile yields.

[4] Consistent recent evidence by Peri and Sasahara (2019) documents that higher temperatures trigger internal migration in middle- but not in low-income countries. Other studies investigating the effects of short-run weather fluctuations on migration across regions find positive effects in Pakistan (Mueller et al. 2014), Mexico (Jessoe et al. 2010), Indonesia (Bohra-Mishra et al. 2014) and Nepal Maystadt et al. (2016). In the context of Brazil, Brunel and Liu (2020) estimate that higher temperatures increase inter-state migration flows.

of population and economic activity (Desmet and Rossi-Hansberg 2015; Balboni 2019; Conte et al. 2021; Nath 2022). The quantitative predictions of these models largely depend on the extent to which factor market frictions constrain the optimal adjustment to climate change. Our finding that asymmetric spatial labor market frictions constrain the factor reallocation process from the agricultural sector in directly affected regions to manufacturing in other regions can be used to inform the values of spatial labor market frictions in counterfactual analysis.

II Conceptual Framework

Our empirical work provides estimates of both the direct and indirect effects of regional climate shocks on factor allocation across sectors: the former occur in regions directly hit by excess dryness, while the latter occur in regions connected to directly hit regions through factor markets.

To interpret our estimates, in this section we present a classic open economy model which permits to study the effects of changes in sectoral productivity and factor supply on equilibrium factor allocation across sectors. The predictions of this model provide for a neoclassical benchmark against which we can interpret the empirical findings. In particular, confronting the model predictions with the data permits to assess whether the observed factor reallocation in response to climate change approximates the optimal adjustment that would take place in a frictionless economy or appears to be driven by factor market frictions.

We start by analyzing the local effects of climate change. For this purpose, we think of each Brazilian municipality as a small open economy producing goods in two traded sectors, agriculture and manufacturing, and a non-traded sector, services. We model climate change as a permanent reduction in local agricultural productivity.[5] Then, we use the model to predict the effects of local agricultural productivity decline on local factor markets, that is, the the direct effects of climate change.

In addition, we theoretically assess the indirect effects of climate change on regions integrated with directly affected ones. Such effects result from labor and capital flows across municipalities in response to changes in relative regional agricultural productivity. Mestieri et al. (2025) provide a detailed analysis of the cross-municipality labor and capital flows triggered by local climate shocks based on full quantitative spatial. Thus, for the purpose of the simple comparative statics exercise we perform based on the framework introduced here, we do not model factor flows explicitly but treat the changes in factor supply as exogenous from the point of view of destination regions.

[5]Note that climate change could also affect productivity in other sectors, but as long as its effect on agricultural productivity is larger, the predictions of the model would be qualitatively similar.

II.A Model Setup

We present a classic small open economy model where goods and factor markets are perfectly competitive. There are two traded sectors, agriculture (a) and manufacturing (m) and one non-traded sector, services (s). Trade costs are assumed to be zero so that prices for agricultural and manufacturing goods are determined in international markets. Preferences over consumption of the three goods are Cobb-Douglas with expenditure shares α_i for each good $i = a, m, s$. There are three production factors in fixed supply within each region: land (T), capital (K) and labor (L). We assume that agricultural production uses the three factors, under constant returns to scale: $Q_a = A_a T_a^{\beta}(K_a^{\gamma} L_a^{1-\gamma})^{1-\beta}$. In turn, manufacturing and services only use capital and labor: $Q_m = A_m K_m^{\gamma} L_m^{1-\gamma}$; $Q_s = A_s K_s^{\gamma} L_s^{1-\gamma}$, where $0 < \beta < 1$, $0 < \gamma < 1$, and A_i are productivity parameters for each sector $i = a, m, s$. Note that because all sectors use capital and labor in the same proportions, we can think of them as a composite mobile factor $X = K^{\gamma} L^{1-\gamma}$. As a result, the model inherits the workings of a textbook Ricardo-Viner (or factor-specific) model as described by Dixit and Norman (1980).[6]

II.B Equilibrium

In this section we describe the main features of equilibrium, which are derived formally in Appendix sections A.A.1 and A.A.2.

II.B.1 Factor prices

Wages and the reward to capital are set by manufacturing. This is because this sector is tradable and has constant returns to scale, so it can expand (contract) in export markets at constant prices and factor rewards. As a consequence, the equilibrium price of services is determined by relative manufacturing productivity $P_s = P_m \frac{A_m}{A_s}$, as in the Balassa-Samuelson effect.

II.B.2 Equilibrium factor allocation across sectors

The equilibrium employment share in agriculture is increasing in its comparative advantage with respect to manufacturing, which is determined by the two classic supply-side forces. First, Ricardian comparative advantage, given by relative agricultural productivity (A_a/A_m). Second, Heckscher-Ohlin comparative advantage, given by land abundance relative to the composite mobile factor $[T/(K^{\gamma}L^{1-\gamma})]$.[7]

[6] For a comprehensive discussion of the predictions of the model in the general case where each sector has a different capital intensity with respect to labor see Corden and Neary (1982). As climate change generates scarcity of productive land, we believe that the most relevant difference between agriculture and other sectors in this context is land-intensity. Thus, the model does not focus on differences in capital use per worker across sectors.

[7] See Appendix equation (A7) for a formal solution of equilibrium employment shares in agriculture.

The employment share in the non-traded service sector is instead determined by local demand. Note that the demand for services is a constant share (α_s) of income ($wL + r_k K + r_T T$). Thus, in equilibrium the employment share in services is increasing in income per-capita, which in turn is a positive function of both agricultural productivity A_a and land abundance.[8]

Finally, employment shares in manufacturing are determined by the labor and capital market clearing conditions ($L_m = L - L_a - L_s$ and $K_m = K - K_a - K_s$).

II.C Effects of climate change on factor allocation across sectors

II.C.1 Direct effects through agricultural productivity

We model climate change as a permanent reduction in local agricultural productivity A_a. Lower agricultural productivity reduces agricultural employment shares of both capital and labor because the comparative advantage of agriculture relative to manufacturing worsens. In addition, it induces a reduction in the employment shares of capital and labor in the service sector because demand for services falls due to lower land income. As a result of these changes, labor and capital reallocate towards manufacturing, whose employment share increases (see Appendix A.B.1 for a proof).

II.C.2 Indirect effects through factor flows

The empirical findings in Mestieri et al. (2025) suggest that climate change affects regions indirectly through factor reallocation across space in response to permanent agricultural productivity declines in directly affected regions. While they explicitly model factor flows in their quantitative framework, we abstract from such flows but instead allow for *within-region* factor flows across different sectors in order to study the changes in the equilibrium factor allocation in response to climate-change-induced factor supply shocks.

Labor. First, we investigate the effects of an inflow of climate migrants on the labor allocation across sectors by considering an increase in the overall local supply of labor without any change in sectoral productivities (i.e. $\hat{A}_a = 0$, $\hat{L} > 0$ and $\hat{K} = 0$). We show in Appendix A.B.2 that in equilibrium, the wage falls and all sectors increase the employment of labor. However, employment grows faster in manufacturing. This is because in the model an increase in the labor endowment reduces land per worker. Then, comparative advantage in agriculture worsens and the agricultural employment share falls for both capital and labor. In turn, land income per worker falls, reducing per-capita demand for services and the employment share of the service sector for both factors. Then, the

[8]See Appendix equation (A10) for a formal solution of equilibrium employment shares in services.

manufacturing employment share of both factors must increase (see Appendix section A.B.2 for a proof).

Capital. Second, motivated by the results of Mestieri et al. (2025), we consider the effect of a reduction in local capital supply (i.e. $\hat{A}_a = 0$, $\hat{L} = 0$ and $\hat{K} < 0$). We show in Appendix A.B.2 that in equilibrium, the reward to capital increases and all sectors reduce the employment of capital. However, capital use falls faster in manufacturing. Note that in the model, the mechanisms are identical to those described above for labor, with an opposite sign.

Table I summarizes the model predictions for the changes in the equilibrium employment levels of labor and capital in all three sectors implied by the direct effect ($\hat{A}_a < 0$) and the indirect effects ($\hat{L} > 0$ or $\hat{K} < 0$).

III Identification strategy

III.A Meteorological variation in dryness across Brazilian regions

Brazil's climate has started experiencing several of the effects of global warming. Figure I reports data from the Climatic Research Unit (CRU) at the University of East Anglia, which shows that the average temperature in Brazil has been steadily increasing since 1920, from 22.5 to 24°C. This trend shows an acceleration in the 1980s when the signal of climate change emerged in all regions of the country: temperature changes became larger than two standard deviations above the average in the baseline period 1850-1900.[9]

Climate models predict that global warming increases precipitation in high and low latitudes but decreases it in middle ones, which encompass the majority of Brazilian regions (IPCC 2021, page 645). The combination of higher temperature and lower precipitation is expected to lead to an increase in the frequency and duration of droughts in Brazil. This trend has been already documented in the climatology literature (Cunha et al. 2019) and is visible in the time series of natural disasters reported by the National System of Civil Protection or SINPDEC (Sistema Nacional de Proteçao e Defesa Civil). The SINPDEC data is based on reports on natural disasters such as droughts and floods filed by municipal authorities to the federal government, which we digitized for the period 2000 to 2018.[10] Figure B1 in the Online Appendix reports the aggregate trends in reported number of natural disasters and shows a marked increase in the number of reported droughts during the last two decades.

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

[10] 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.

Figure B2 shows the geographical distribution of reported droughts across Brazil in the 2000-2010 period (panel a) and 2011-2018 period (panel b). Although droughts are reported all over the country, reports tend to be clustered in the inner region of the Northeast of Brazil, as well as in the inner regions of the South and in the eastern regions of the Amazon area. This variation across regions and time in the frequency of droughts suggests that although climate change affects all regions in the country, it has heterogeneous effects across regions.

As a measure of regional changes in climate we use deviations in average drought conditions between a given decade and the past century. In particular, we rely on a meteorological measure of dryness, the Standardized Precipitation and Evapotranspiration Index, or SPEI (Vicente-Serrano et al. 2010). The index compares the amount of precipitation in a given area with its potential evapotranspiration needs, which are a function of local temperature.[11] Crucially for our purposes, SPEI measures standard *deviations* of dryness relative to the historical average observed in a given locality.[12] Thus, SPEI has been used by the climatological literature to predict droughts caused by climate change (Dubrovsky et al. 2009; Vicente-Serrano et al. 2010). Indeed, SPEI well predicts the timing of drought reports recorded in SINPDEC, which indicate dry conditions considered so extreme by local authorities to require federal assistance (Mestieri et al., 2025).

We calculate SPEI as standard deviations in dryness in a given Brazilian municipality in each year within the period 2000 to 2018 relative to the previous century (1901-1999). In the rest of the paper, we define our measure of deviation of dryness relative to historical averages as $\Delta Dryness = SPEI \times -1$, so that an increase in the index captures an increase in excess dryness. In Figure II, we report the geographical distribution of average $\Delta Dryness$ in the 2001-2010 decade and the 2011-2018 decade. Consistently with the increase in the frequency of reported droughts described above, excess dryness has increased over the past two decades and displays large variation across regions. We exploit this regional heterogeneity to construct a differences-in-differences empirical strategy to identify the potential effects of climate change on local factor markets.

As reported by Mestieri et al. (2025), changes in average dryness in the first decade of the 2000s relative to historical averages display a weaker correlation with initial characteristics of municipalities compared to reported droughts. Table B1 in the Online Appendix shows that the correlation between excess dryness during the 2001-2010 pe-

[11] Potential evapotranspiration is defined as the evaporation from an extended surface of a short green crop which fully shades the ground, exerts little or negligible resistance to the flow of water, and is always well supplied with water. Note that this land use is assumed when computing the index regardless of actual land use. SPEI captures the climatic water balance in a given location, with positive values indicating a water surplus (precipitation larger than PET) and negative values indicating a water deficit (precipitation smaller than PET).

[12] SPEI is a standardized index, i.e. SPEI equal to -1 in year t implies that the difference between observed rain and potential evapotranspiration needs in year t are one standard deviation lower than the average observed in the baseline period in a given locality.

riod and baseline municipality characteristics is substantially lower than the correlation between reported droughts and the same characteristics.

Mestieri et al. (2025) also report the distribution of $\Delta Dryness$ across Brazilian municipalities in the first and second decade of the 2000s and show that, while the distribution of dryness in the first decade is centered around its average observed in the previous century, dryness appears to be drawn from a warmer distribution in the second decade. This is consistent with the trend reported in Figure B1, which shows an increase in the frequency of droughts across Brazilian regions during the last ten years relative to the previous decade. As in this previous work, all quantifications in the paper are computed for a municipality moving from the median to the 90^{th} percentile of excess dryness, which corresponds to about 1 standard deviation in the 2000-2010 decade, and to 1.36 standard deviations in the 2011-2018 decade.

III.B Regression specification based on Census Data

We first study the direct and indirect long-run effects of excess dryness on factor reallocation across sectors using decadal Census data from 2000 and 2010 combined with the dryness index SPEI and municipality controls. Our regression specification resembles the equation derived as an approximation of the full structural system of equations obtained from solving the quantitative spatial equilibrium model in Mestieri et al. (2025). However, we use outcome variables that are disaggregated at the sector-region level and run separate regressions by sector. In particular, we estimate the following differences-in-differences specification:

$$\begin{aligned}
\Delta y_{l,s,2000-2010} &= \alpha_{r,s} + \beta_{1,s} \underbrace{\Delta Dryness_{l,2001-2010}}_{\text{Direct effect}} \\
&+ \sum_{f=L,K} \beta_{2,s}^{f} \underbrace{Exposure_{l,2001-2010}^{f}}_{\text{Indirect effects}} + \Lambda_s X_{l,s,t=1991} + \varepsilon_{l,s}, \qquad (1)
\end{aligned}$$

where l indexes municipalities and r indexes one of the five macro-region of Brazil (North, Northeast, Central-West, South and Southeast).[13] The outcome variable $\Delta y_{l,s,2000-2010}$ captures decadal variation in the outcomes of interest at municipality-sector level between 2000 and 2010. As in Mestieri et al. (2025), $\Delta Dryness_{l,2001-2010}$ is the average level of dryness experienced by a municipality over the years 2001 to 2010, in deviation from the level of dryness historically recorded in a given municipality over the last century as described in section III.A. The term $Exposure_{l,2001-2010}^{f}$ captures the exposure of a given municipality to the excess dryness experienced over the same decade by municipalities integrated with l via capital and labor markets.

[13]As in Mestieri et al. (2025), 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.

III.B.1 *Exposure via capital market integration*

The measure capturing exposure through capital market integration, $Exposure^{K}_{m,2001-2010}$ follows the methodology proposed in Bustos et al. (2020), and it is based on the assumption that two municipalities are more financially integrated if they both have branches of the same bank, which would be the case if there is any friction in the interbank market that banks solve through internal capital markets. The measure is defined as

$$Exposure^{K}_{lt} = \sum_{b \in B_l} w_{bl} BankExposure_{bt}, \tag{2}$$

with

$$BankExposure_{bt} = \sum_{l \in O_b} \omega_{bl} \Delta Dryness_{lt},$$

where the weights ω_{bl} are the share of total loans of bank b coming from origin municipality l in the baseline year 2000, and O_b is the set of origin municipalities in which bank b was present in 2000. The weights w_{bl} capture the lending market share of bank b in municipality l and are constructed as the value of loans issued by branches of bank b in l divided by the total value of loans issued by branches of all banks operating in l (whose set we indicate with B_l) in the baseline year 2000. A detailed discussion of the a identification assumptions is provided in Mestieri et al. (2025).

III.B.2 *Exposure via labor market integration*

To capture labor market integration, we construct internal migration flows based on a question in the Census asking respondents for their municipality of residence five years prior to the Census year. Thus, using the 2000 Census, we calculate bilateral migration flows between each pair of municipalities during the period 1995-2000. The foundation of this measure is the notion that migrants tend to follow the paths of previous migrants because social network reduce migration costs, for example due to previous migrants facilitating job referrals to later migrants from the same origin (Altonji and Card 1991; Card 2001).

Following the approximation of the model-derived structural equation in Mestieri et al. (2025), we construct the exposure to changes in excess dryness via migration links as

$$Exposure^{L}_{lt} = \frac{M_{l,2000}}{L_{l,2000}} \sum_{l' \neq l} \alpha_{l,l'} \Delta Dryness_{l',2001-2010} \tag{3}$$

with

$$\alpha_{l,l'} = \frac{1}{2} \frac{M_{1995-2000,l' \to l} + M_{1995-2000,l \to l'}}{\sum_l [M_{1995-2000,l' \to l} + M_{1995-2000,l \to l'}]},$$

where $M_{1995-2000,l' \to l}$ and $M_{1995-2000,l \to l'}$ represent the size of migration flows between municipality pairs in the period 1995 to 2000, $M_{l,2000}$ is the total number of migrants in l as of 2000, and $L_{l,2000}$ is the population of l in 2000. The weights $\alpha_{l,l'}$ capture the degree of connection via past migrants between two municipalities.

III.C Estimating indirect effects through labor market integration using employer-employee data

To fully disentangle the indirect effects of excess dryness via labor market connections from other mechanisms, we propose an additional and novel identification strategy that exploits variation in flows of migrant workers across firms located in the same municipality using the employer-employee dataset RAIS. These data contain information on all formal workers in Brazil, allowing us to follow workers across firms, sectors and locations.[14]

We start by constructing a measure of the degree of labor market integration between each municipality in Brazil and a given firm using past migration flows as follows:

$$\alpha_{oi(m),t^*} = \frac{L_{i(m),t^*,o\rightarrow d}}{L_{i(m),t^*}} \tag{4}$$

where $\alpha_{oi(m),t^*}$ is the share of workers employed in the baseline year t^* in firm i whose last observable move was from origin municipality o to the destination municipality m, the one where the employer i is located in year t^*. When mapping equation (4) to the data, we construct past workers' movements using the period 1998 to 2005, and define our baseline year $t^* = 2005$.

Next, we use this measure to predict future worker flows between origin municipality o and destination firm $i(m)$. The rationale is the same as the one described in section III.B.2. 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.

Then, we estimate the following specification at the firm-origin level:

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

[14] 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 focus on 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, we focus on the one with the highest salary, so that each individual appears only once in each year (Bustos et al. 2020; Dix-Carneiro and Kovak 2017; Helpman et al. 2017)

The outcome variable in equation (5) is the flow of migrant workers from a given origin municipality o to firm i located in destination m (where $o \neq m$) between 2006 and 2010, normalized by the total number of workers of firm $i(m)$ observed on average in the same period. This flow is regressed on the measure of the baseline exposure of firm $i(m)$ to migrants from a given region, and an interaction of such exposure with excess dryness that occurred in the origin between 2006 and 2010. To make the estimation computationally less intensive, we aggregate all potential origin municipalities in two groups: origins that experienced very high excess dryness during the 2006-2010 period, which we define as those in the top quartile of $\Delta Dryness$, and those that did not. Municipalities in the top quartile experienced, on average, 0.76 of a standard deviation higher excess dryness than those in the rest of the distribution in the same years.

Constructing a measure of exposure to migrant flows at the firm-municipality of origin level allows us to exploit variation across firms that operate in the same destination municipality, and thus control for any unobservable common shock in the destination labor market. It also allows us to saturate the model presented in equation (5) with firm fixed effects. This effectively absorbs any heterogeneity in firm-level shocks, so that the coefficient of interest β_2 captures within-firm variation in migrant workers' flows from regions that are heterogeneously affected by excess dryness.[15] When estimating equation (5) we cluster standard errors at the destination municipality level to account for spatial correlation of the error terms across firms operating in the same location.

IV Results

IV.A The effects of excess dryness on agriculture

To study the impact of dryness on the agricultural sector, we consider two main outcome variables: area farmed and value of agricultural production (both in log changes). Agricultural outcomes are sourced from the yearly Agricultural Production Survey (PAM) carried out by the Brazilian Statistical Institute (IBGE). Data is collected by the IBGE via questionnaires administered by an IBGE agent to local producers and intermediaries operating in the agricultural sector, and the method is designed to generate a sample representative of the production of the main crops farmed in each municipality. The survey covers the major temporary and permanent crops farmed in Brazil, including information on area planted, area harvested and value of production. Because new crops have been added to PAM over time, we focus our analysis on the ten largest crops by area planted, which include soybean, maize, sugar, wheat, rice, beans, cotton, coffee, cassava and potato. These ten crops are consistently covered by the survey during the period under study and collectively represent 88% of area farmed in the average municipality.

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

Mestieri et al. (2025) estimate both a panel regression over the time period 2000-2018 as well as a specification based on long-run changes similar to equation (1). Their panel estimation results indicate that municipality moving from the median to the 90th percentile experiences an 8 percent decline in both area farmed and value of agricultural production, confirming that excess dryness relative to usual meteorological conditions causes sizable output losses in the agricultural sector. They also show that the reduction in agricultural output is non-linear in the level of excess dryness with municipalities in the top decile of the distribution of excess dryness suffer a loss of 16 percent in the value of agricultural production relative to those in the middle of the distribution. This suggests that the negative impact of dryness is driven by municipalities that experienced higher dryness relative to their historical, while the relationship between dryness and agricultural output is flat in the part of the dryness distribution below the historical average.

Given the focus on changes in long-run dryness condition in this paper, we only display the results based on a long-run specification in Table II. The outcome variable is the long-run change in agricultural outcomes observed in a given municipality between the year 2000 and the year 2018, while the explanatory variable captures the change between the average dryness experienced during the 2001 to 2018 period and the dryness experienced during the reference period 1901-1999 in a given municipality. We find that a prolonged period of excess dryness relative to historical averages has large and significant effects on agricultural production. A municipality moving from the median to the 90th percentile of excess dryness relative to its historical average experienced declines in agricultural area farmed of about 15% and in total value of agricultural production of 23% in the last two decades. Results are similar when only focusing on the top 10 crops. These magnitude suggest limited adaptation responses to climate change by the agricultural sector.

As seen in Figure III, the reduction in agricultural output is non-linear in the level of excess dryness. Municipalities in the top decile of the distribution of excess dryness suffer a loss of 14 percent in the value of production relative to those in the middle of the distribution, while municipalities in the bottom decile experience no significant change. This indicates that while extremely dry conditionsâwhich are driven by higher temperatures and lower rainfallârelative to historical averages are detrimental for agricultural production, lower temperatures and higher rainfall have on average non-significant effects.

IV.B The effects of excess dryness on capital allocation

We study the long-run effects of direct and indirect exposure to excess dryness by estimating equation (1) where the outcome variables are long-run changes in loans at municipality level between 2000 and 2010. We focus on this decade to match the analysis on labor reallocation using the Population Census years presented in section IV.C.

For regulatory reasons, loans to the agricultural sector are recorded separately from total loans. This allows us to study the effect on agriculture vs non-agricultural lending separately, although, unlike for employment outcomes, we are not able to further separate the non-agricultural sector between manufacturing and services. Also, note that loans and deposits of both firms and individuals are reported together in the ESTBAN data. This has the advantage of including loans to individual farmers running their farms and the disadvantage of pooling together production and consumption loans.

The estimation results are presented visually in Figure IV and reported in detail in Table III. Panel (a) of the figure shows the direct effects on loans, separately for the agricultural and non-agricultural sector, corresponding to the coefficient estimates in the first row in columns 1 and 2 of Table III. We find that excess dryness generates lower lending to both sectors in directly affected regions. A municipality moving from the median to the 90th percentile of average excess dryness over the 2001 to 2010 period experienced a 10 and 15 percent decline in the balance of outstanding loans to the agricultural and non-agricultural sector, respectively.

Turning to indirect effects via migrants in panel (b) of Figure IV and the second row of Table III, we find positive estimates for both sectors. However, the effect on agricultural loans is imprecisely estimated and just about half of the effect on non-agricultural loans, which is 12 percent. This suggests that a positive shock to labor supply via incoming migrants leads to both increased loan supply by local banks and a reallocation towards the non-agricultural sector.

In contrast, as show in in panel (c), regions exposed to excess dryness via their links to other regions through the bank branch network experience a significant decline in lending that is of similar size for both sectors. The magnitudes are about half the size of the direct effect on agricultural loans, and precisely estimated.

To interpret these findings, we use the benchmark neoclassical model presented in section II and its predictions summarized in Table I. In directly affected regions, the model predicts that a reduction in agricultural productivity reallocates capital away from agriculture and services into manufacturing. This can explain the sharp reduction in agricultural loans observed in the data. However, we also see a large reduction in lending to non-agriculture. This result implies that manufacturing is not absorbing the credit released by the agricultural sector. There are two potential reasons for this result. Manufacturing might display some degree of decreasing returns to scale so that the equilibrium return to capital falls in the region. This would generate capital outflows towards other regions. However, we do not observe capital inflows into regions financially connected to areas experiencing an increase in dryness as coefficients on the exposure via the banking network are negative for both sectors. Thus, a neoclassical framework cannot fully explain our empirical findings.

A plausible alternative mechanism behind the finding that capital flows out of both directly and indirectly affected regions is highlighted by Mestieri et al. (2025) and a key feature of their spatial equilibrium model. Their empirical analysis based on a yearly panel specification exploiting short-term weather shocks reveals that regions financially connected to areas experiencing droughts are providing insurance in the short run through bank loans. However, when these droughts are not temporary but turn out to persist over a decade, affected regions might be unable to repay their loans, reducing the liquidity of those banks operating in them.[16] If there are frictions in the interbank market, those banks might reduce lending everywhere, including branches located in regions not affected by excess dryness, as suggested by the estimation results of the long-run specification provided in Mestieri et al. (2025).[17]

This credit disruption channel can generate a negative spillover from agriculture to local manufacturing and to all sectors in other regions. To see this, consider the predictions of our benchmark model for the effect of a reduction in capital supply on factor allocation across sectors. As shown in the last row of Table I, a lower total capital supply reduces capital employment in all sectors, but more than proportionally in manufacturing. This prediction is consistent with the large reduction in non-agricultural loans both in directly affected regions and and those indirectly affected via banks documented in Figure IV. It is also consistent with the findings documented in panel (c) of Figure V, which shows that the negative indirect effect of exposure to excess dryness via the bank network on employment is concentrated in the manufacturing sector.

To summarize, these findings provide new insights on the role of the banking sector in capital reallocation across sectors due to climate change. While Mestieri et al. (2025) show that the financial system favors risk sharing in regions affected by weather shocks with the support of financially connected regions in the short run, the long-run evidence stands in sharp contrast with the predictions of classical open economy models. Those models predict that as persistent increases in dryness reduce agricultural productivity, capital should reallocate towards local manufacturing or other regions. However, we find capital reallocation away from both local agriculture and non-agriculture. This suggests that persistent increases in dryness not only reduce investment in agriculture, but also have negative spillovers on local non-agricultural sectors, in addition to the negative spillovers on credit availability for both sectors in regions financially connected through bank branch networks.

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

[17] The banking literature has highlighted that for liquidity shocks to propagate within the bank branch network two frictions are necessary: (i) banks must have imperfect access to external financing; (ii) information frictions must channel credit in locations where banks have an informational advantage, such as locations where they have existing branches. Evidence on how liquidity shocks propagate within bank internal capital markets via the bank branch network has been shown, among others, in Bustos et al. (2020) in the context of Brazil and Gilje et al. (2016) in the context of the US.

IV.C The effects of excess dryness on labor allocation

We now turn to Population Census data to analyze the impact of excess dryness on labor reallocation across local sectors in the 2000 to 2010 decade. As in section IV.B, we estimate equation (1) in order to capture two types of effects. First, due to the local impact of exceptionally dry weather on agricultural productivity, which potentially also affects other sectors through general equilibrium effects, excess dryness directly affects local labor markets. Second, when a spatial reallocation of factors occurs, regions that are not directly affected by dryness but destinations or origins of factors that move might also experience changes in their allocation of labor across sectors. Note that Census data allows us to observe both formal and informal workers. This is particularly important when studying the impact of excess dryness on the agricultural sector, which is characterized by high levels of informality.

The predictions of the benchmark model presented in Section II is that a permanent reduction in agricultural productivity in a region will generate a reallocation of labor away from agriculture and services and towards manufacturing both in directly affected regions and in regions connected via labor markets. We can test this by estimating equation (1) with changes in log employment in the agricultural, manufacturing and service sectors as outcome variables.[18]

The estimates of the direct and indirect effects of excess dryness on the allocation of labor across sectors are summarized in Figure V and reported in detail in columns 3-5 of Table III. The results on the direct effects across sectors are in line with the predictions of our model reported in the first row of Table I. We find a large and negative direct effect of excess dryness on agricultural employment. Municipalities at the 90th percentile of excess dryness experience a 4.7 percent larger decline in agricultural employment between 2000 and 2010 than those at the median. Services also experience a significant decline of 2.8 percent in directly affected areas, while local manufacturing absorbs some of the displaced workers. A simple back of the envelope calculation indicates that only about a third of the workers released by agriculture, services and other sectors relocate locally into manufacturing. The remaining workers either migrate – as documented in Mestieri et al. (2025) – or remain unemployed locally. Recall that Census data includes both formal and informal labor, and therefore any reallocation across sectors that also entails a reallocation to or from informality is captured in the estimates of Table III.

As shown in panel (b) of Figure V, we find that regions more exposed to climate migrants expand employment in all sectors but that the effect on manufacturing employment is smaller than for the other sectors and imprecisely estimated. More specifically, relative to those at the median, municipalities at the 90th percentile of exposure to excess dryness via the migrant network experience increases of 2.4 and 2.1 percent in agriculture

[18]The following residual subsectors are not included in any of the three broad sectors we consider: public sector, extractive industry and utilities.

and services, respectively, while the effect for manufacturing employment is an insignificant 1.8 percent. This implies a decline in the share of manufacturing employment in regions indirectly exposed to excess dryness via migration. Recall that in the frictionless benchmark presented in section II, the manufacturing sector should increase in relative terms both in regions directly affected and in regions indirectly affected by excess dryness. This asymmetry in the ability of manufacturing to absorb workers across regions could be driven by a mismatch between the skills of climate migrants and the skills required for employment in manufacturing in major destination regions, or by frictions in the allocation of labor displaced by excess dryness. We investigate these mechanisms in the following sections.

Finally, as noted in the previous section, panel (c) of Figure V indicates that exposure to excess dryness via banks leads to fall in employment that is almost exclusively driven by the manufacturing sector, which declines by over 9 percent for a region at the 90th percentile relative to one at the median of exposure via banks.

The findings discussed above suggest that when agricultural workers who lost their jobs due to excess dryness stay in their region of origin, they tend to find jobs in the local manufacturing sector. However, when they migrate to other regions they are more likely to find jobs in agriculture or services. This finding might be driven by the fact that climate migrants lack the skills required for employment in manufacturing in major destination regions. In this case, the absence of migrant reallocation into manufacturing would reflect an optimal allocation of labor at destination.

To investigate this mechanism, we categorize workers into two skill types based on their level of education reported in the Population Census. We define high-skill workers as those that have at least completed high-school, i.e. have 12 years of education. Table IV reports the results on the direct and indirect effects of excess dryness on the allocation of labor across sectors separately for low-skill workers (Panel A) and high-skill workers (Panel B).

We find that the direct effects of excess dryness are similar between the two types: both are displaced from agriculture and services and relocate into manufacturing. When we focus on the indirect effects, we find that low-skill workers are more likely to relocate into the agricultural sector, while high-skill workers are more likely to relocate into services. These results can easily be rationalized by the fact that agriculture tend to be more low-skill intensive (7% high-skill labor share at baseline) than services (37% high-skill labor share at baseline). However, we find that both worker types do not relocate into manufacturing at destination, despite this sector having a similar skill intensity as services (35%). This finding suggests the existence of labor market frictions that affect the assignment process of climate migrants to jobs at destination. In the last part of the paper, we investigate potential sources of such frictions using employer-employee level data.

V Results on Labor Allocation using employer-employee data

We now discuss micro-based evidence on the indirect effects of excess dryness via migrant networks obtained using employer-employee data. We rely on the identification strategy described in section III.C, which exploits variation in flows of migrant workers across firms in the same destination municipality. The use of employer-employee data allows us to explore in more detail potential frictions preventing the reallocation of workers into manufacturing in destination municipalities predicted by the model.

We start by exploring to what extent the connections via migrant networks to regions exposed to excess dryness vary across firms in different sectors. We compute the average level of such connections across firms in a given sector by taking the average of the interaction of interest in equation (5) – $\alpha_{oi(m)} \times 1(Dry)_o$ –, i.e. the interaction between the share of migrant workers from each origin and a dummy capturing regions more exposed to excess dryness in the 2006-2010 period.

Figure VI reports average connections by sector. The key finding is that firms in agriculture tend to be more connected to regions more exposed to excess dryness via their network of past migrant workers. The average firm in agriculture has, at baseline, 6 percent of workers coming from regions that experienced high excess dryness in the 2006-2010 period, about three times more than firms in the manufacturing sector (2 percent), while the average connection of firms in services is somewhat in between (4 percent). In short: agriculture has the highest initial connection to areas more affected by excess dryness, while manufacturing has the lowest. This stylized fact underlines a potential explanation for the lack of reallocation of climate migrants into manufacturing in indirectly affected regions.[19]

Notice that if the geographical distribution of excess dryness is as-good-as-randomly assigned across Brazilian municipalities, the lower connection of manufacturing firms suggests that they are in general less connected to any region via migrant networks, potentially because they are more likely to be geographically clustered and to source their employees locally. This stylized fact is visible in Figure VIII, which shows the geographical distribution of the employment share of each sector across Brazilian municipalities. Despite agriculture and manufacturing employ a similar number of workers in the country as a whole, and thus have a similar share of aggregate employment, their degree of geographical concentration across space is very different. While agricultural workers are

[19] A potential concern with the stylized fact presented in Figure VI (a) is that it only applies to formal workers recorded in RAIS but it is not robust to including informal workers, the majority of the labor force in agriculture. In Figure VII, we recompute the degree of connection to regions more exposed to excess dryness in the 2006-2010 period using data from the 2000 Population Census. Although we do not observe the firm employing each worker, Census data allows us to observe the municipality of origin of each worker five year prior to the Census, the current sector of employment and whether a worker is formally or informally employed. Figure VII shows that the stylized fact presented in Figure VI (a) applies to both formal and informal workers.

spread across most municipalities in the country, manufacturing workers tend to be concentrated in a limited number of geographical clusters, mostly in the South and Central regions of Brazil.

Finally, in Figure IX, we report average connections to regions experiencing excess dryness for firms in different size categories: micro (less than 10 employee), medium (10 to 49 employees), and large (50 employees and above). Differences in the intensity of connections to regions more exposed to climate change are less stark but still present across the firm size distribution. On average, the degree of initial connection with areas experiencing high excess dryness is increasing in size, with large firms' initial connections being about 30% higher than those of small firms.

Table V reports the results of estimating equation (5). The objective of this analysis is to compare firms in the same destination municipality, and study whether those initially more connected to regions more affected by climate change also experience larger inflows of workers from those regions. In column (1), we estimate a version of equation (5) with origin fixed effects, destination municipality fixed effects and our measure of exposure to migrants from a given region as explanatory variables. The estimated coefficient β_1 indicates that, in the 2006-2010 period, firms receive larger flows of migrant workers from regions with which they were initially more connected. The magnitude of the coefficient indicates that firms with a 10 percent larger initial connection to a certain origin municipality experience a 6 percent larger flow of workers from that region. This magnitude describes the increase in flows relative to other firms operating in the same destination municipality.

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

Even within a given destination municipality, firms more connected to areas with higher excess dryness via past migrant workers might be more connected to those areas also via trade networks or financial links. If that is the case, then the coefficient β_2 cannot be interpreted as capturing the indirect effect of excess dryness on firms' employment via labor reallocation. Thus, in column (3), we estimate equation (5) including firm fixed effects. We find that, when fully accounting for firm-level differences, the estimated coefficient β_2 remains positive and increases in magnitude, which indicates that other firm-level connections with areas with high excess dryness tend to have a negative effect on firm growth.

In columns (4)-(6) we split our sample by sector. The differential increase in worker flows from areas with high excess dryness is relatively similar across sectors, with larger coefficients for agriculture than manufacturing and services. As documented in Figure VI, agricultural firms tend to be on average more connected to affected areas via their past workers' flows. As shown in Figure X (a), our estimates indicate that agricultural firms with average connection to areas with high excess dryness experience a 2.2 percent larger flow of workers from such regions.[20] This effect is about three times larger than the one observed for firms in manufacturing (0.7 percent) and services (0.8).

How much of the differences in the effect of excess dryness on firm employment is attributable to the lack of initial connections to such regions? To quantify the impact of differences in this type of spatial frictions across sectors, we propose a counterfactual analysis in which we assign to all sectors the average level of initial connections to regions experiencing high increase in dryness observed in our sample. The results of this analysis are visualized in Figure X (b). When removing heterogeneity in the initial connections across sectors, the effect of excess dryness on employment declines in agriculture and services, while it increases in manufacturing, as predicted by the benchmark framework. In terms of magnitude, the effects for agriculture decreases from 2.2 to 1.3 percent and for services from 1.1 to 0.9 percent, while in manufacturing it increases from 0.6 to 1 percent. This implies that equalizing spatial frictions across sectors changes the size of the effects in the direction predicted by the conceptual framework without frictions presented in section II.

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

Overall, these results are consistent with the existence of frictions driving the reallocation of workers displaced by permanent increases in dryness in the Brazilian labor market. First, the results indicate that climate-driven labor reallocation can retard the structural transformation process in destination regions. Largely due to spatial frictions, 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). Second, the impact of pre-existing connections on flows is larger for small firms. Small firms tend to be characterized by lower skill intensity and lower average wages – characteristics that in the literature have been associated with lower productivity.[21]

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

[21] See Lucas (1978) and 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

VI Concluding Remarks

This paper studies how climate change reshapes the spatial and sectoral allocation of labor and capital in a developing economy. Using detailed data from Brazil, we analyze how persistent increases in excess dryness affect credit and labor allocation across sectors locally as well as in regions linked through financial and labor markets to those that are directly hit. Our analysis builds on Ponticelli et al. (2025) by moving beyond aggregate outcomes and focusing on the sectoral dimension of adjustment, with particular emphasis on the role of manufacturing in absorbing factors displaced from agriculture.

We document four main findings. First, persistent increases in excess dryness generate a large contraction in lending to both agricultural and non agricultural firms. This contraction operates both directly, in municipalities experiencing higher excess dryness, and indirectly, in municipalities financially integrated with affected areas through bank branch networks. In contrast, municipalities exposed to excess dryness through migration links experience an expansion in lending, particularly outside the agricultural sector, consistent with higher labor inflows raising demand for credit in manufacturing.

Second, increases in excess dryness lead to large employment declines in the agriculture and manufacturing sectors while manufacturing expands, thereby absorbing part of the displaced workforce. This indicates that within-region sectoral reallocation broadly follows the efficient adjustment path predicted by standard neoclassical models of structural transformation.

Third, regions financially connected to those hit by excess dryness experience sharp declines in manufacturing employment. This result mirrors the contraction in lending observed in financially integrated regions and is consistent with the model prediction that reductions in overall capital lead to a reallocation of labor out of manufacturing and into remaining sectors.

Fourth, spatial reallocation of labor across regions is severely distorted by factor market frictions. Migrants from drought-affected regions are disproportionately absorbed by agriculture and services rather than manufacturing in destination municipalities, despite the model prediction that manufacturing should expand when labor inflows increase. These patterns point to the presence of asymmetric spatial labor market frictions that limit the ability of manufacturing firms to absorb migrant workers.

Taken together, these findings highlight a key constraint on adaptation to climate change. While local sectoral reallocation from agriculture to manufacturing is relatively unconstrained, spatial reallocation of labor and capital toward manufacturing is hindered by financial frictions and spatial labor market frictions. As a result, climate change slows structural transformation not only by reducing agricultural productivity, but also by distorting the allocation of displaced factors across regions and sectors, increasing the

and quantity based measures of total factor productivity.

aggregate costs of adjustment relative to frictionless benchmarks.

Our results have important policy implications. Policies that strengthen the resilience of financial intermediation and reduce frictions in inter-regional labor matching can play a central role in facilitating adaptation to climate change. Improving access to credit in regions receiving migrants, easing informational and hiring barriers faced by manufacturing firms, and enhancing the integration of regional labor markets may allow economies to better exploit the gains from structural transformation. More broadly, our findings underscore the importance of incorporating spatial labor and capital market frictions into quantitative frameworks used to evaluate the long-run economic costs of climate change and the potential gains from adaptation policies.

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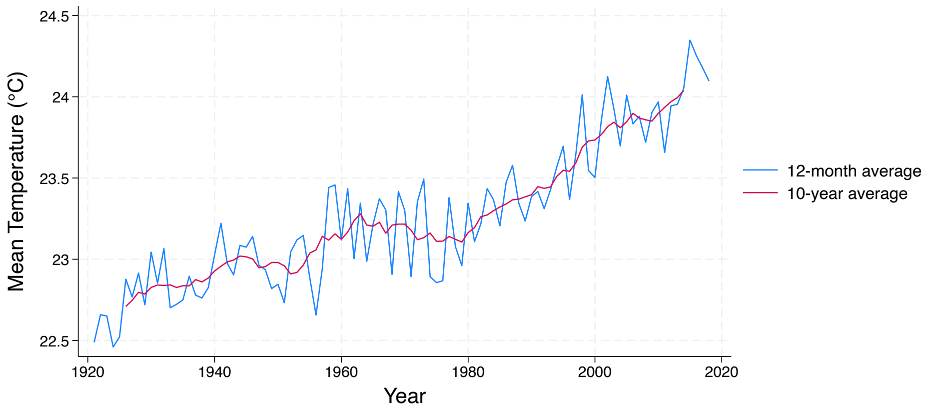
Figures

Figure I: Average temperature in Brazil since 1920

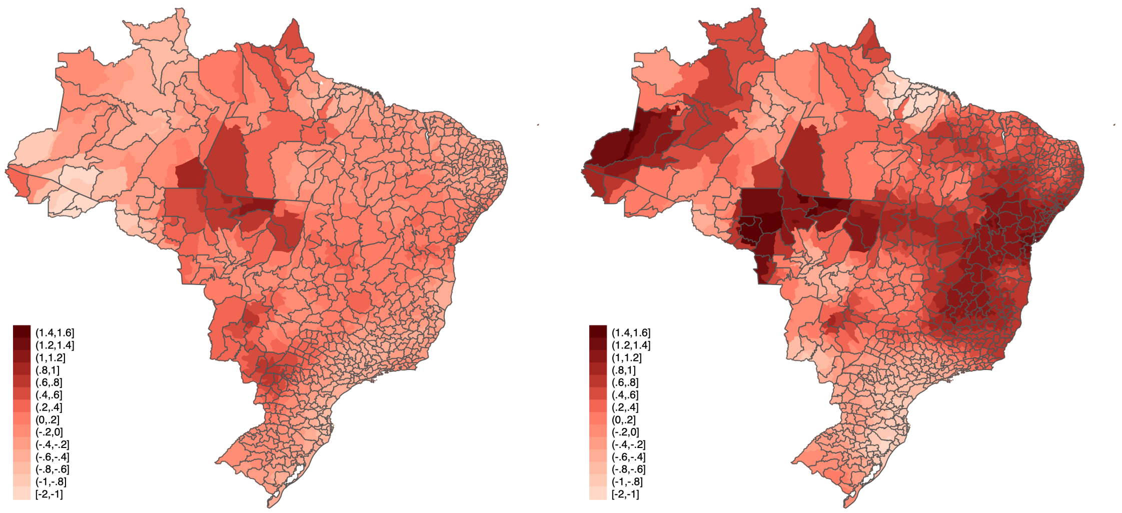


Source: Climatic Research Unit, University of East Anglia.

Figure II: Geographical distribution of SPEI

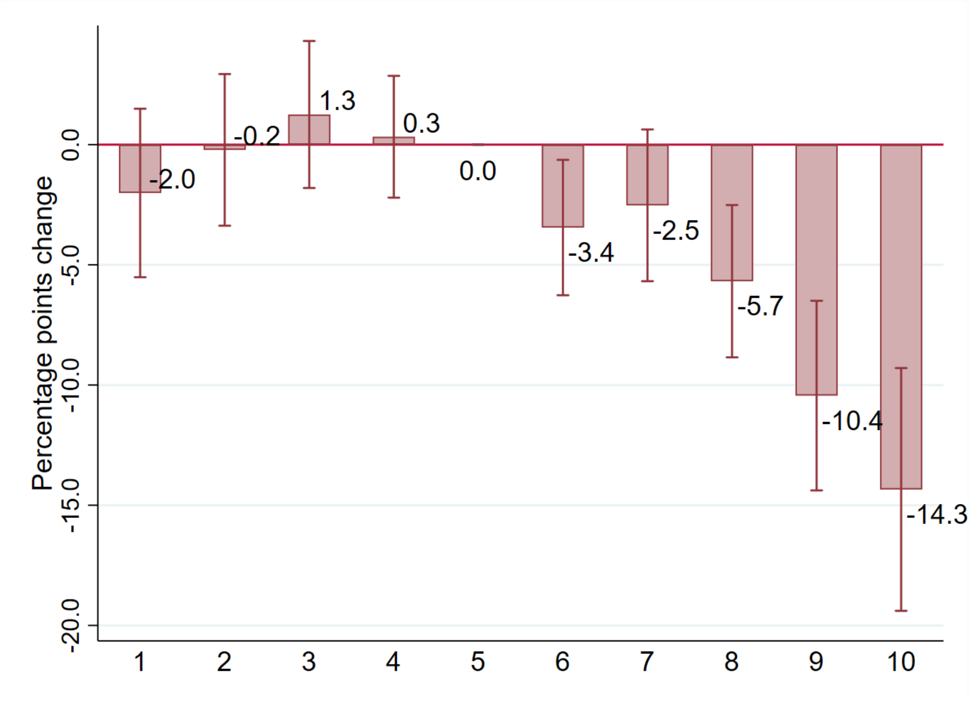
Excess dryness index

(a) 2000-2010 (b) 2011-2018



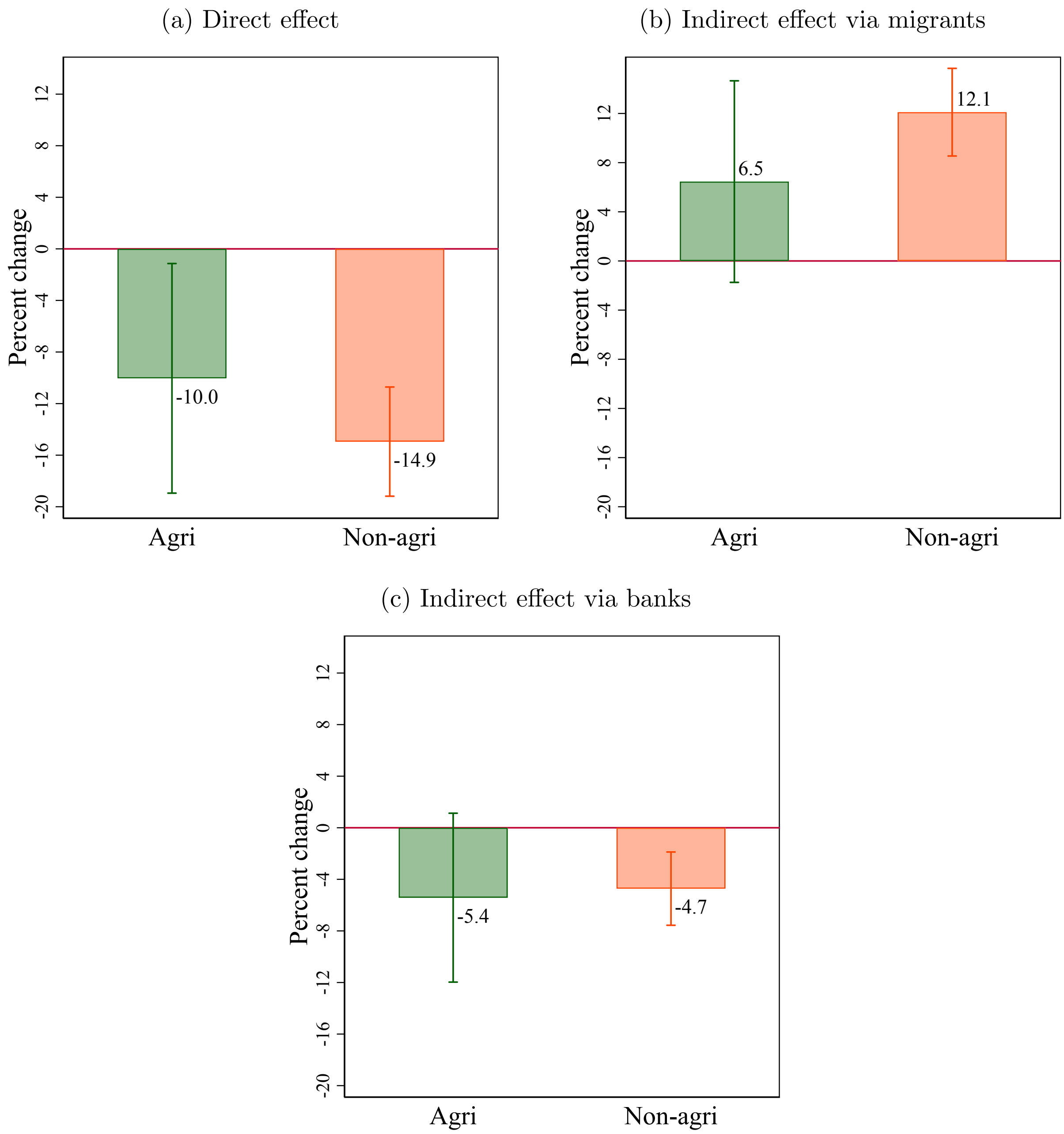
Notes: Maps show the excess dryness index (average SPEI multiplied by -1) during the indicated time period as well as the borders of the 558 microregions of Brazil, the level of clustering of standard errors used in the empirical analysis to account for spatial correlation in the error term.

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



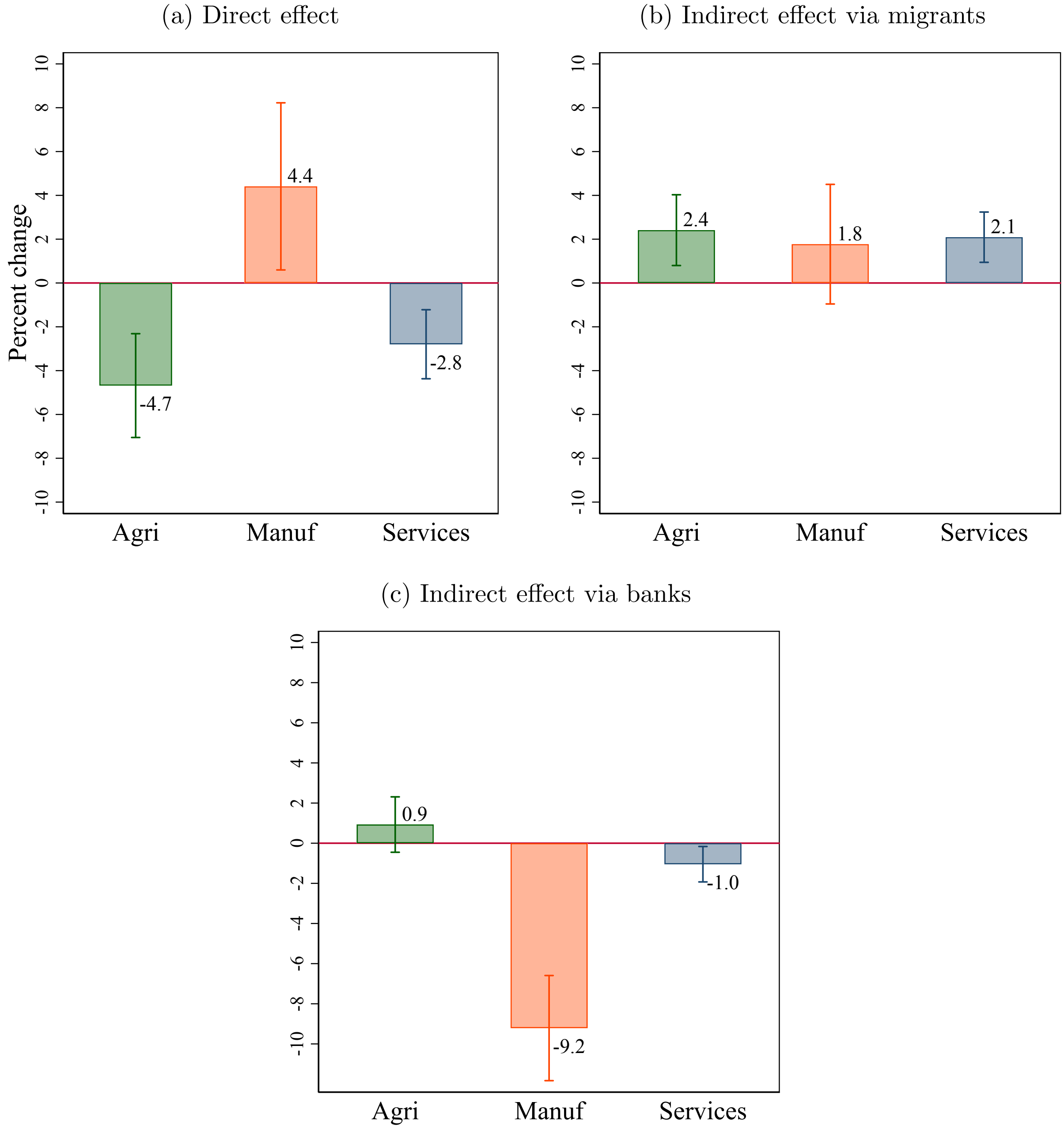
Notes: The figure shows the estimated coefficients on dummies capturing deciles of the excess dryness index in a panel regression at municipality-year level for the period 2000 to 2010 where the outcome variable is the log value of agricultural production recorded in the PAM survey. Deciles of $Dryness$ go from the wettest to the driest. Estimated effects are relative to the 5^{th} decile. Controls include AMC fixed effects, macro-region times year fixed effects and the share of population living in rural areas, log income per capita, literacy rate, population density, deforestation and changes in soy and maize potential yields, each interacted with year dummies. Vertical lines are 95 percent confidence intervals.

Figure IV: Effects of Excess Dryness on Loans by sector



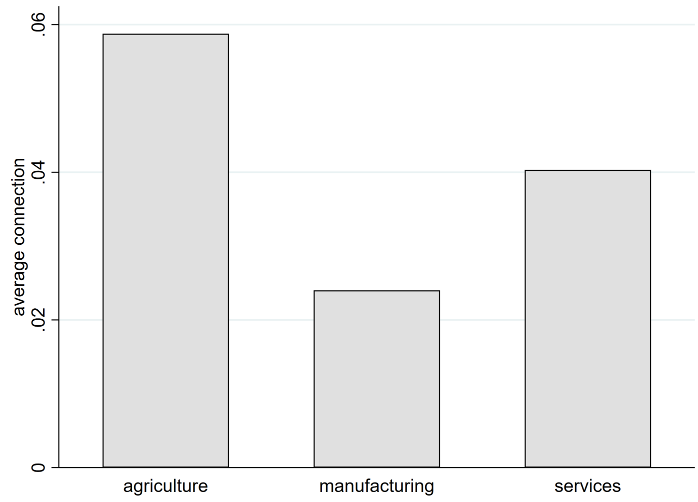
Notes: The figure reports the estimated effects on the change in log loans to the agricultural and non-agricultural sector between 2000 and 2010 for a municipality going from the 50th to the 90th percentile in the direct and indirect (exposure via migrant and bank network) measures of excess dryness.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

Figure V: Effects of Excess Dryness on Employment by sector



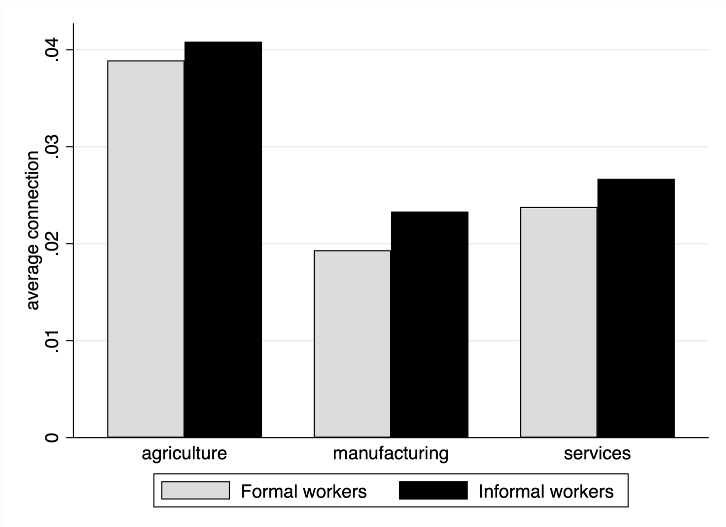
Notes: The figure reports the estimated effects on the change in log employment in each sector between 2000 and 2010 for a municipality going from the 50th to the 90th percentile in the direct and indirect (exposure via migrant and bank network) measures of excess dryness. Controls include macro-region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

Figure VI: Firm Initial Connections to High Excess Dryness Areas



Notes: The figure shows the average interaction $\alpha_{oi(m)} \times 1(Dry)_o$ across firms in each sector. The first element of the interaction ($\alpha_{oi(m)}$) is calculated as the share of workers employed in the baseline year 2005 whose last observable move was from origin municipality o to firm i in destination municipality m. The second term of the interaction ($1(Dry)_o$) is a dummy capturing municipalities in the top quartile of dryness in the 2006-2010 period. We weight each firm by its number of workers at baseline.

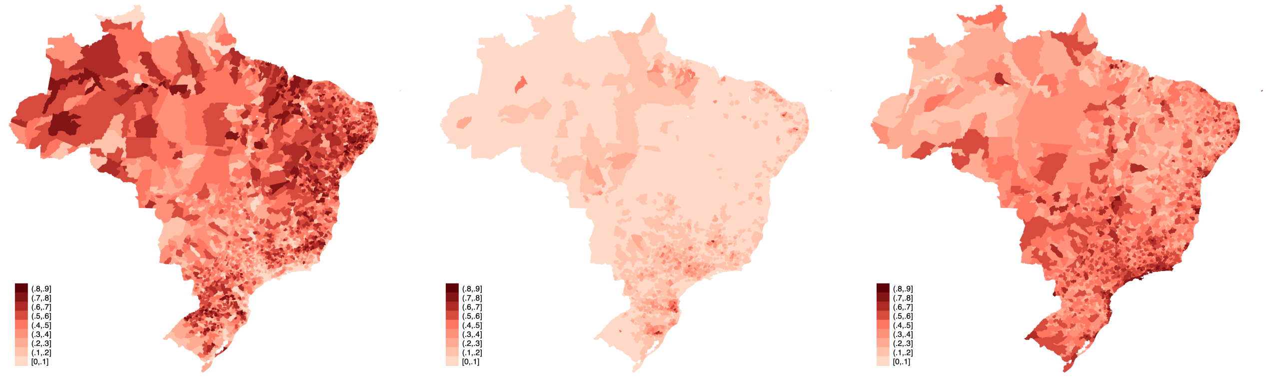
Figure VII: Municipality Initial Connections to High Excess Dryness Areas



Notes: The figure shows the average connection α_{om} of municipalities m to origins o that are in the top quartile of dryness by sector. The connection is calculated as the share of workers employed in the baseline year 2000 who moved from origin municipality o to the destination municipality m during the preceding 5 years.

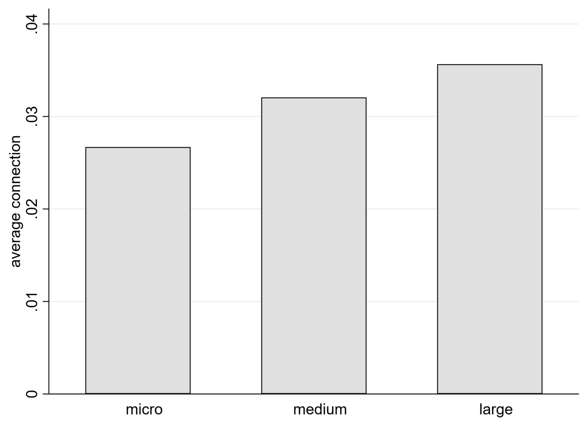
FIGURE VIII: GEOGRAPHICAL DISTRIBUTION OF SECTORAL EMPLOYMENT SHARES

(a) Agriculture (b) Manufacturing (c) Services



Notes: The maps show the employment in the indicated sector as a share of overall employment in each municipality.

FIGURE IX: FIRM INITIAL CONNECTIONS TO HIGH EXCESS DRYNESS AREAS

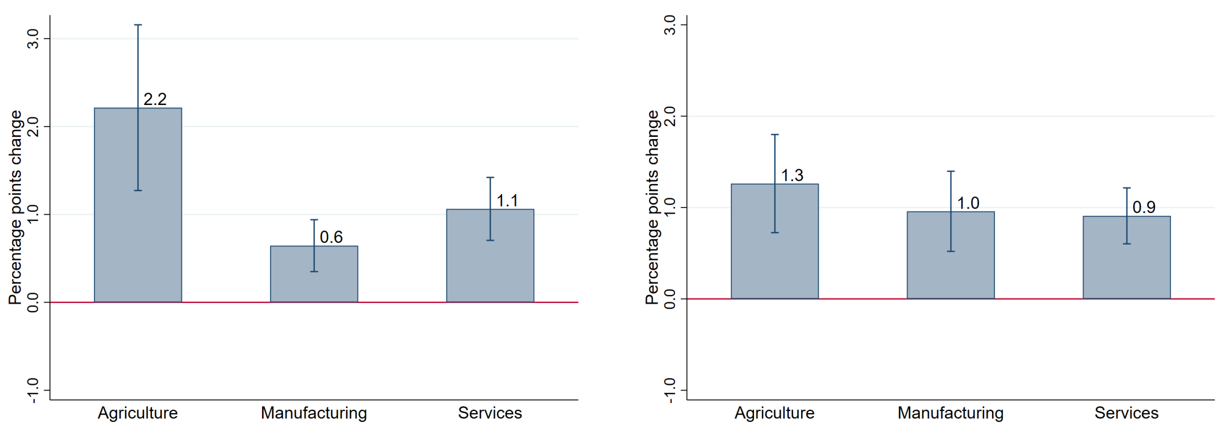


Notes: The figure shows the average interaction $\alpha_{oi(m)} \times 1(Dry)_o$ across firms by size category. The first element of the interaction ($\alpha_{oi(m)}$) is calculated as the share of workers employed in the baseline year 2005 whose last observable move was from origin municipality o to firm i in destination municipality m. The second term of the interaction ($1(Dry)_o$) is a dummy capturing municipalities in the top quartile of dryness in the 2006-2010 period. We weight each firm by its number of workers at baseline.

Figure X: Firm exposure and employment growth

(a) Sector-specific spatial frictions

(b) Counterfactual with symmetric spatial frictions across sectors



Notes: Panel (a) reports the effect of *Dryness* on employment growth for firms with the average connection to areas with excess dryness observed in their sector. Panel (b) reports the effect of *Dryness* on employment growth under the counterfactual scenario in which all sectors are assigned the average connection to areas with excess dryness observed in the sample.

Tables

Table I: Model predictions

		Agriculture		Manufact.		Services	
Direct effect	$\hat{A}_a < 0$	$L_a \downarrow$	$K_a \downarrow$	$L_m \uparrow$	$K_m \uparrow$	$L_s \downarrow$	$K_s \downarrow$
Indirect effects	$\hat{L} > 0$	$L_a \uparrow$	$K_a \downarrow$	$L_m \uparrow\uparrow$	$K_m \uparrow$	$L_s \uparrow$	$K_s \downarrow$
	$\hat{K} < 0$	$L_a \uparrow$	$K_a \downarrow$	$L_m \downarrow$	$K_m \downarrow\downarrow$	$L_s \uparrow$	$K_s \downarrow$

Notes: This table shows the predicted equilibrium changes in the two mobiles factors employed in each sector after the change indicated in the first column. Two arrows indicate a more than proportional change in the factor employed in the respective sector (implying less than proportional changes in the remaining sectors).

Table II: The Effect of Excess Dryness on Agricultural Outcomes

VARIABLES	(1) Δ log area planted all crops	(2) Δ log area planted top 10 crops	(3) Δ log value production all crops	(4) Δ log value production top 10 crops
Δ Dryness 2001-2018	-0.149***	-0.120***	-0.226***	-0.238***
	(0.0248)	(0.0272)	(0.0274)	(0.0314)
Observations	4,196	4,167	4,186	4,155
R-squared	0.235	0.248	0.236	0.290
Region FE	y	y	y	y
Controls	y	y	y	y

Notes: Standard errors clustered at the microregion level (558) reported in parenthesis. Controls include: the share of population living in rural areas, log income per capita, literacy rate, population density, deforestation, and changes in soy and maize potential yields.

Table III: Effect of Dryness by Sector 2000-2010

Outcomes:	Δlog Loans		Δlog Employment		
	agri	non-agri	agri	manuf	serv
	(1)	(2)	(3)	(4)	(5)
Avg Dryness, 2001-2010	-0.100*	-0.149***	-0.047***	0.044*	-0.028***
	(0.054)	(0.026)	(0.014)	(0.023)	(0.010)
Exposure to Dryness via migrants	0.065	0.121***	0.024**	0.018	0.021***
	(0.050)	(0.022)	(0.010)	(0.017)	(0.007)
Exposure to Dryness via banks	-0.054	-0.047***	0.009	-0.092***	-0.010*
	(0.040)	(0.017)	(0.008)	(0.016)	(0.005)
Observations	2,334	2,795	4,247	4,240	4,247
R-squared	0.167	0.225	0.095	0.100	0.142
Macro-region FE	y	y	y	y	y
Controls	y	y	y	y	y

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

Table IV: Effect of Dryness on Employment by Sector and Skill Level 2000-2010

Panel A: Low-skill workers

Outcomes:	Δlog Employment		
	agri	manuf	serv
	(1)	(2)	(3)
Avg Dryness, 2001-2010	-0.0791***	0.0593**	-0.0411***
	(0.0153)	(0.0256)	(0.0104)
Exposure to Dryness via migrants	0.0415***	-0.000452	0.0275***
	(0.0114)	(0.0198)	(0.00841)
Exposure to Dryness via banks	0.00832	-0.0988***	-0.00634
	(0.00915)	(0.0178)	(0.00659)
Observations	4,247	4,247	4,247
R-squared	0.117	0.067	0.114
Macro-region FE	y	y	y
Controls	y	y	y

Panel B: High-skill workers

Outcomes:	Δlog Employment		
	agri	manuf	serv
	(1)	(2)	(3)
Avg Dryness, 2001-2010	-0.0774**	0.0878***	-0.0587***
	(0.0311)	(0.0309)	(0.0148)
Exposure to Dryness via migrants	0.00621	-0.00711	0.0390***
	(0.0234)	(0.0272)	(0.0125)
Exposure to Dryness via banks	0.0551***	-0.0409	0.0399***
	(0.0182)	(0.0249)	(0.00976)
Observations	4,247	4,247	4,247
R-squared	0.312	0.073	0.350
Macro-region FE	y	y	y
Controls	y	y	y

Notes: Standard errors clustered at the microregion level (558) reported in parenthesis. Coefficient estimates refer to a municipality moving from the 50th to the 90th percentile of the distribution of dryness or exposure to dryness. Controls include: the share of population living in rural areas, log income per capita, literacy rate, population density, deforestation level, changes in soy and maize potential yields, and exposure to Dryness via road network. Workers are categorized into high- vs low-skill based on the education level reported in the Population Census. We defined high-skill workers as those that have at least completed high-school (i.e. 12 years of education).

Table V: Workers' Flows to Firms Exposed to Dryness

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

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

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

A Model Derivations

There are three factors in fixed supply. Land (T) is only used in agriculture, while capital (K) and labor (L) are used by the three sectors in the same proportions. The production functions for the three sectors are

$$Y_a = A_a T^{\beta} \left(K_a^{\gamma} L_a^{1-\gamma}\right)^{1-\beta} \tag{A1}$$
$$Y_m = A_m K_m^{\gamma} L_m^{1-\gamma} \tag{A2}$$
$$Y_s = A_s K_s^{\gamma} L_s^{1-\gamma} \tag{A3}$$

Note that for notational convenience we define the composite factor $X = K^{\gamma} L^{1-\gamma}$.

A.A Equilibrium

A.A.1 Factor prices

Cost minimization implies $\frac{K_i}{L_i} = \frac{\gamma}{1-\gamma}\frac{w}{r_k}$ for all sectors i. Then, factor market equilibrium implies

$$\frac{K_i}{L_i} = \frac{K}{L} = \frac{\gamma}{1-\gamma}\frac{w}{r_k} \tag{A4}$$

According to equation (A4), the reward to capital can be written as a function of the wage and relative factor endowments: $r_k = \frac{L}{K}\frac{\gamma}{1-\gamma}w$.

Profit maximization in manufacturing and services implies $P_m A_m = P_s A_s = c_x(w, r_k)$, where the unit cost function for the composite factor X is $c_x(w, r_k) = \delta r_k^{\gamma} w^{1-\gamma}$ with $\delta = \left(\frac{\gamma}{1-\gamma}\right)^{1-\gamma} + \left(\frac{1-\gamma}{\gamma}\right)^{\gamma}$.

The exogenous price P_m of manufacturing determines the price of services $P_s = \frac{P_m A_m}{A_s}$. In addition, if we substitute $r_k = \frac{L}{K}\frac{\gamma}{1-\gamma}w$, the exogenous P_m determines the equilibrium wage and rental rates as

$$w = A_m P_m (1-\gamma)\left(\frac{K}{L}\right)^{\gamma}$$
$$r_k = A_m P_m \gamma \left(\frac{L}{K}\right)^{1-\gamma}$$

Thus, factor prices are only functions of manufacturing productivity and the capital intensity of production, and thus independent of the factor allocation across sectors. This is because all sectors display identical capital demand per worker.

A.A.2 Equilibrium factor allocation across sectors

Given (A4), in equilibrium it must be the case that all sectors have identical employment shares of labor and capital: $\frac{K_i}{K} = \frac{L_i}{L}$. Using the definition of the composite factor we can write: $\frac{X_i}{X} = \left(\frac{K_i}{K}\right)^{\gamma} \left(\frac{L_i}{L}\right)^{1-\gamma}$. Then we obtain

$$\frac{X_i}{X} = \frac{K_i}{K} = \frac{L_i}{L} \tag{A5}$$

This implies we only need to solve for the employment share of the composite factor in each sector.

Agriculture Profit maximization in agriculture implies

$$\begin{aligned} P_a MPT_a &= r_T \\ P_a MPX_a &= c_x(w, r_k) \\ P_a A_a (1-\beta) T_a^{\beta} X_a^{-\beta} &= c_x(w, r_k) \end{aligned}$$

Substituting the cost functions with the condition for profit maximization in manufacturing and using the land market clearing condition gives:

$$X_a^* = \left[(1-\beta)\frac{A_a}{A_m}\frac{P_a}{P_m}\right]^{\frac{1}{\beta}} T \tag{A6}$$

$$\frac{X_a^*}{X} = \left[(1-\beta)\frac{A_a}{A_m}\frac{P_a}{P_m}\right]^{\frac{1}{\beta}} \frac{T}{X} \tag{A7}$$

Therefore, the ratio of land rents to the unit cost of the composite factor is

$$\frac{r_T}{c_x} = \frac{\beta}{1-\beta}\frac{X_a}{T} = \frac{\beta}{1-\beta}\left[(1-\beta)\frac{A_a}{A_m}\frac{P_a}{P_m}\right]^{\frac{1}{\beta}} \tag{A8}$$

Services Aggregate demand for services is

$$P_s C_s = \alpha_s \left(wL + r_k K + r_T T\right)$$

where α_s is the consumption expenditure share on services.

Substituting the cost minimization equality $wL + r_k K = c_x X$, the price of services $P_s = c_x / A_s$ and the equilibrium condition $C_s = Y_s = A_s X_s$, we obtain the composite factor demand in services

$$X_s = \alpha_s \left(X + \frac{r_T}{c_x} T\right) \tag{A9}$$

$$\frac{X_s}{X} = \alpha_s \left(1 + \frac{r_T}{c_x}\frac{T}{X}\right) \tag{A10}$$

Manufacturing Labor and capital factor market clearing imply:

$$\frac{L_m}{L} = 1 - \frac{L_a}{L} - \frac{L_s}{L}$$
$$\frac{K_m}{K} = 1 - \frac{K_a}{K} - \frac{K_s}{K}$$

which together with (A5) yields:

$$\frac{X_m}{X} = 1 - \frac{X_a}{X} - \frac{X_s}{X} \tag{A11}$$

A.B Comparative statics

In what follows, we compute the equilibrium effects of log deviations of model parameters from their initial values, denoted by $\hat{Z} \equiv d \log Z$.

A.B.1 Direct effects at origin

First, we consider the equilibrium effects of a change in local agricultural productivity: $\hat{A}_a$.

Differentiating (A6), we obtain

$$\hat{X}_a^* = \frac{1}{\beta}\hat{A}_a$$

Differentiating (A8) and recalling that c_x is only a function of manufacturing productivity and prices, we obtain

$$\hat{r}_T = \frac{1}{\beta}\hat{A}_a$$

Thus, differentiating (A9) and defining $s_T = \frac{r_T T}{X + r_T T}$, we obtain

$$\hat{X}_s = s_T \hat{r}_T = s_T \frac{1}{\beta}\hat{A}_a$$

Finally, differentiating the factor market clearing condition for the composite factor yields

$$\hat{X}_m = -\frac{X_a}{X_m}\hat{X}_a - \frac{X_s}{X_m}\hat{X}_s = -\frac{X_a}{X_m}\frac{1}{\beta}\hat{A}_a - \frac{X_s}{X_m}s_T\frac{1}{\beta}\hat{A}_a$$

Note that with constant factor supplies, (A5) implies $\hat{L}_i = \hat{K}_i = \hat{X}_i$ for $i = a, m, s$. Then, as agricultural productivity declines, both capital and labor flow out of agriculture and services and into manufacturing. Because factor supplies are constant, employment shares of both factors fall in agriculture and services and increase in manufacturing.

A.B.2 Indirect effect at destination

Next, we consider the effect of changes in the mobile factor supplies: $\hat{L}$ and $\hat{K}$.

Agriculture employment shares L_a^*/L and K_a^*/K: (A7) implies that as the supply of labor or capital increases, the relative abundance of land falls, comparative advantage in agriculture is reduced and the agricultural employment share of both labor and capital falls according to (A5). A fall in the supply of labor or capital has the opposite effect.

Service employment shares L_s^*/L and K_s^*/K: (A10), (A8) and (A5) imply that as the supply of labor or capital increases, the service sector employment share of both capital and labor falls. This is because land per unit of the composite factor falls, so land income falls relative to the composite factor income. A fall in the supply of labor or capital has the opposite effect.

Manufacturing employment share L_m^*/L and K_m^*/K: (A11) and (A5) imply that the employment shares of all factors in manufacturing increase (decrease) with a rise (fall) in the supply of labor or capital.

Agriculture employment levels L_a and K_a:

Suppose that due to relatively larger inflow or outflow of one of the mobile factors, the capital intensity K/L changes. Then the factor market equilibrium condition (A4) implies that w/r_k must change. Still, note that $c_x(w, r_k)$ is determined by manufacturing prices and productivity, thus it is independent of factor supplies. This implies that in equilibrium wages and the rental price of capital change in opposite directions. To see this, differentiate c_x to obtain $\hat{c}_x = \gamma \hat{r}_k + (1-\gamma)\,\hat{w} = 0$.

Next, differentiate the factor market clearing condition (A4) to get $\hat{w} - \hat{r_k} = \hat{K} - \hat{L}$ and substitute this in the equation just above to find a solution for the changes in factor prices:

$$\hat{w} = \gamma \left(\hat{K} - \hat{L}\right)$$
$$\hat{r}_k = -(1-\gamma)\left(\hat{K} - \hat{L}\right)$$

Equation (A6) implies that the composite factor employed in agriculture remains fixed: $\hat{X}_a = \gamma \hat{K}_a + (1-\gamma)\,\hat{L}_a = 0$.

Solving this equation for $\hat{L}_a$ and using $\hat{K}_a - \hat{K}_a = \hat{K}_a - \hat{K}_a$ from differentiating (A4), we obtain

$$\hat{L}_a = \gamma \left(\hat{L} - \hat{K}\right)$$
$$\hat{K}_a = (1-\gamma)\left(\hat{K} - \hat{L}\right)$$
$$(L_a \hat{/} L) = (\gamma - 1)\,\hat{L} - \gamma \hat{K}$$
$$(K_a \hat{/} K) = (\gamma - 1)\left(\hat{L}\right) - \gamma \hat{K}$$

- Suppose that $\hat{L} > 0$ and $\hat{K} = 0$. Then, the labor and capital employment shares in agriculture fall. Labor flows into agriculture and capital leaves the sector as $\hat{L}_a > 0$ and $\hat{K}_a < 0$.

- Suppose that $\hat{L} = 0$ and $\hat{K} < 0$. Then, the labor employment and capital employment shares in agriculture increase. Labor flows into agriculture and capital leaves the sector as $\hat{L}_a > 0$ and $\hat{K}_a < 0$.

Service employment levels L_s and K_s:
First, we differentiate equation (A9):
$\hat{X}_s = \alpha_s \frac{X}{X_s} \hat{X}$.
$\hat{X}_s - \hat{X} = \left(\alpha_s \frac{X}{X_s} - 1\right) \hat{X}$.
Therefore, using (A5), have

$$\hat{L}_s - \hat{L} = \left(\alpha_s \frac{X}{X_s} - 1\right) \left[\gamma \hat{K} + (1-\gamma) \hat{L}\right]$$

with $0 < \alpha_s \frac{X}{X_s} < 1$.

- Suppose that $\hat{L} > 0$ and $\hat{K} = 0$. Then, we obtain $\hat{L}_s = \left[\left(\alpha_s \frac{X}{X_s} - 1\right)(1-\gamma) + 1\right] \hat{L}$, where we always have that $\left(\alpha_s \frac{X}{X_s} - 1\right)(1-\gamma) + 1 > 0$. Thus, labor flows into services, although less than proportionally to increase in labor supply. In turn, capital must leave the service sector, as the capital supply is fixed and we showed above that the capital employment share in the sector falls.

- Suppose that $\hat{L} = 0$ and $\hat{K} < 0$. Then, $\hat{X}$ falls and as shown above, the labor employment and capital employment shares in services increase. Analogous calculations as those for labor above imply that labor flows into services and capital leaves the sector, less than proportionally to the reduction in capital supply.

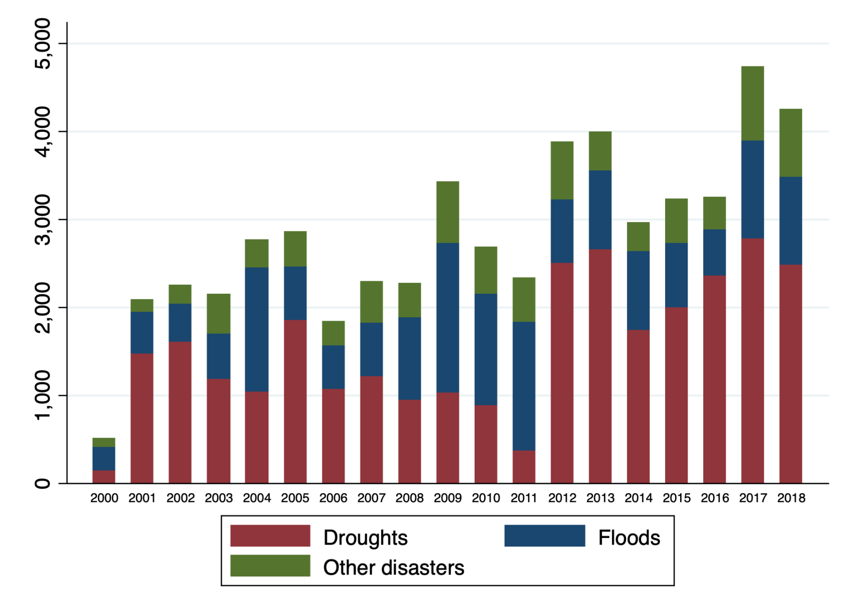
Manufacturing employment levels L_m and K_m:

- Suppose that $\hat{L} > 0$ and $\hat{K} = 0$. When labor supply increases, employment shares of both factors increase given the results for agriculture and services and equation (A11). Thus, capital flows in and labor flows in more than proportionally to the increase in labor supply.

- Suppose that $\hat{L} = 0$ and $\hat{K} < 0$. When capital supply falls, employment shares of both factors fall, again given the results for agriculture and services and equation (A11). Labor flows out and capital flows out more than proportionally to the fall in capital supply.

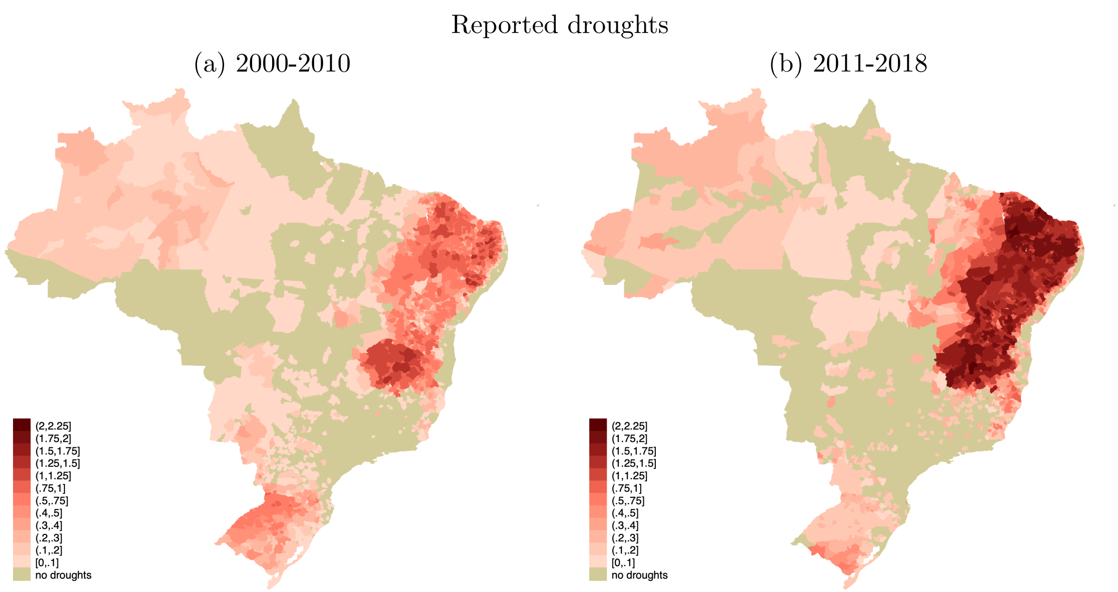
B Additional Figures and Tables

Figure B1: Reported Natural Disasters By Year: 2000-2018



Source: Sistema Nacional de Proteçao e Defesa Civil - SINPDEC

Figure B2: Geographical distribution of reported droughts



Notes: Maps show the average number of reported droughts per year during the indicated time period.

Table B1: Balance Test

	N Droughts	Δ Dryness	Exposure via migrants	Exposure via banks
Rural Share	0.075***	0.026	0.020	0.014*
	(0.014)	(0.016)	(0.012)	(0.007)
Log Income per Capita	-0.164***	-0.071**	-0.041*	-0.038**
	(0.047)	(0.034)	(0.022)	(0.016)
Literacy rate	-0.043***	-0.014*	0.001	-0.006*
	(0.012)	(0.008)	(0.005)	(0.003)
Log Pop Density	-0.479***	-0.456***	0.057	0.018
	(0.103)	(0.101)	(0.084)	(0.059)
Soy Suitability	0.032**	0.043***	-0.035***	-0.018**
	(0.013)	(0.016)	(0.010)	(0.009)
Maize Suitability	0.133***	0.106**	-0.093***	-0.041
	(0.047)	(0.047)	(0.029)	(0.026)
Deforestation	-0.008	-0.004	0.000	-0.001
	(0.005)	(0.003)	(0.001)	(0.001)

Notes: The table reports estimated coefficients of regressions that have as outcome variables the municipality characteristics observed at baseline (in standard deviations, sourced from the Population Census of 1991) reported in rows, and as explanatory variables the measures of dryness or exposure to dryness via labor and capital markets reported in each column. For baseline measures of soy and maize productivity we use soy and maize potential yields under low inputs as defined in Bustos, Caprettini and Ponticelli (2016). Standard errors clustered at the microregion level (558) reported in parenthesis.