

The Effects of Climate Change on Labor and Capital Reallocation

Christoph Albert

Paula Bustos

Jacopo Ponticelli

Collegio Carlo Alberto

CEMFI and CEPR

Northwestern, NBER and CEPR*

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Abstract

Climate change is expected to reduce agricultural productivity in most developing countries. Classic international trade and geography models predict that the optimal adaptation response is a reallocation of capital and labor from agriculture towards other sectors and regions gaining comparative advantage. In this paper, we provide direct evidence on the effects of recent changes in climate in Brazil to understand to what extent factor market frictions constrain this reallocation process. First, we document that when a region experiences a temporary drought, the agricultural sector obtains insurance through capital flows coming from financially integrated regions. However, if droughts become persistent, we observe a sharp reduction in credit to all sectors in both drying regions and financially integrated regions. Second, persistent increases in dryness generate a large reduction in agricultural employment. Some workers reallocate towards local manufacturing and others out-migrate, as predicted by classical models. In contrast, climate migrants are mostly allocated to small firms outside of manufacturing in destination regions.

Keywords: Droughts, SPEI, Brazil, Migration, Financial Integration.

JEL codes: O1, Q54, O16, J61.

*Albert: Collegio Carlo Alberto, christoph.albert@carloalberto.org. Bustos: CEMFI and CEPR, paula.bustos@cemfi.es. Ponticelli: Northwestern University, NBER and CEPR, jacopo.ponticelli@kellogg.northwestern.edu. We received valuable comments from Rodrigo Adao, Guy Michaels, Remi Jedwab, Chris Udry, Dean Karlan, Seema Jayachandran, Sean Higgins, Steven Helfand, Francisco Lima Cavalcanti, and seminar participants at NBER/BREAD Development Conference, CEPR Development Conference, CEPR Paris Symposium (International Trade), CEPR Annual Symposium in Labour Economics, Stanford Conference on Firms, Trade and Development, Trade & Development EOS conference, King's College Workshop on Trade and Development, LSE Environmental Week, AEA, UEA North American Meeting, IX Workshop on Structural Transformation and Macroeconomic Dynamics, CEBRA, Graduate Institute Geneva, Toulouse School of Economics, Northwestern University, Cornell University, CEMFI, Universitat Pompeu Fabra, Collegio Carlo Alberto, Central Bank of Brazil, ITAM, University of Zurich, USC Riverside, Joint OECD and European Commission Global Forum on Productivity. We are extremely grateful to Ana Paula Cunha for sharing the SPI data for Brazil. Matheus Sampaio provided excellent research assistance. Ponticelli gratefully acknowledges financial support from FIMRC at the Kellogg School of Management. We are grateful to acknowledge financial support from the European Research Council Starting Grant 716388.

I INTRODUCTION

The fast pace of climate change is one of the major challenges of our time. Global warming is expected to increase the frequency of extreme weather events and to generate heterogeneous changes in precipitation patterns across the earth (IPCC, 2021). International trade and geography models predict that as global warming changes the productivity distribution, economic activity reallocates towards sectors and regions gaining comparative advantage. For example, worsening drought conditions in subtropical areas are expected to reduce agricultural productivity and generate a reallocation of agricultural workers towards local manufacturing or less affected regions.¹ However, developing countries are characterized by labor and capital market frictions.² To what extent these frictions can constrain factor reallocation in response to climate change is an open question on which we have scarce evidence. In this paper, we provide direct empirical evidence by studying the effects of recent changes in climate in Brazil on factor reallocation across sectors and regions.

Brazil is particularly suited for this analysis because its climate has already started experiencing the effects of global warming highlighted by climate science. Average temperatures have increased 1°C since 1980, which is above the normal range of variation in the area.³ In addition, climate models predict a reduction in precipitation in most Brazilian regions, which is already visible in the increase in the frequency of droughts reported by municipalities to the federal government during the last two decades.⁴ We exploit the heterogeneous increase in dryness across regions to estimate its local effects on labor and capital allocation across sectors. In addition, we directly measure the effects of increases in dryness on factor flows across regions. Finally, we exploit differences in labor and capital market integration across regions to estimate the spillover effects of increases in dryness on regions that are the destination of those factor flows.

We measure climate change as decadal deviations in dryness relative to the past century, driven by changes in both temperature and rainfall. In particular, we rely on a meteorological measure of dryness, the Standardized Precipitation and Evapotranspira-

¹Economic geography models showing how local shocks to sectoral productivity induce factor reallocation across sectors or regions include Allen and Arkolakis (2014), Fajgelbaum and Redding (2022), Redding and Sturm (2008), Adao, Arkolakis, and Esposito (2019a).

²On the aggregate implications of factor market frictions in developing countries see the seminal work of Banerjee and Duflo (2005) and Caselli (2005a). See Donovan et al. (2023) for recent evidence on labor market frictions in developing countries, and Lagakos (2020) for a review. Even in the context of a developed economy like Germany, Heise and Porzio (2022) document the role of spatial frictions in labor allocation both within and across regions.

³The 2021 report of the International Panel on Climate Change highlights that temperature changes in most regions of Brazil started to be two standard deviations above the baseline period 1850-1900 in the 1980s (IPCC 2021, page 133 and 246).

⁴Climate models predict that global warming will increase precipitation in high and low latitudes but decrease it in middle ones, which encompass the majority of Brazilian regions (IPCC 2021, page 645). We digitized municipality-level data from the National System of Civil Protection in Brazil (SINPDEC) which shows large variation across regions and time in the frequency of droughts.

tion Index, or SPEI (Vicente-Serrano et al., 2010). We document large variation in this measure across Brazilian municipalities, and show that deviations in excess dryness are “as-good-as-randomly assigned” in the sense that they are uncorrelated with initial municipality characteristics such as income per-capita or urbanization. This permits to construct a differences-in-differences empirical strategy to identify the effects of climate change on factor allocation.

The empirical analysis aims at studying both the *direct effects* of excess dryness on the local labor and capital markets of affected municipalities, and its *indirect effects* on municipalities whose factor markets are integrated with areas suffering excess dryness. We construct a measure of capital market integration across municipalities using the structure of bank branch networks and track changes in banks’ capital allocation across municipalities and sectors using balance sheet data from all bank branches in Brazil (ESTBAN). In turn, we construct a measure of labor market integration across municipalities using past migrant networks and track contemporaneous migration flows using Population Census data. Finally, we construct a firm-level measure of labor market integration with each municipality using the employment histories of migrant workers and track contemporaneous worker flows across regions, sectors and firms using social security data from the Annual Social Information System (RAIS).

To interpret our estimates of the direct and indirect effects of excess dryness on factor reallocation across sectors, we develop a classic small open economy model describing the local labor and capital markets of each municipality. We use the predictions of the model as a neoclassical benchmark to assess whether the observed response of factor allocation to climate change approximates the optimal adjustment that would take place in a frictionless economy or appears to be driven by factor market frictions. In this neoclassical framework, factor allocation across the traded 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-traded service sector depends on local demand, which is a function of local income per capita.

In this neoclassical setup, we think of the direct effect of excess dryness as a reduction in local agricultural productivity. This 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 agriculture and services into local manufacturing. The model also generates predictions for the indirect effects of excess dryness in regions which are the destination of factor flows. In particular, we think of these factor flows as a permanent change in the supply of labor (capital), which is exogenous from the point of view of the destination region. Then we use the model to predict the resulting changes in the equilibrium factor allocation across sectors. In particular, an inflow of labor (capital) reduces land per worker and thus the comparative advantage of the agricultural sector. In addition, lower land per worker reduces income per capita and

the relative demand for services. As a result, the indirect effect of dryness through labor (capital) inflows is that the manufacturing employment share of both labor and capital increases.

We start our empirical analysis by documenting that, indeed, regions subject to abnormally dry meteorological conditions experience a significant reduction in agricultural production. These effects are particularly strong for regions experiencing persistent increases in dryness in the last two decades relative to the previous century. A municipality moving from the median to the 90th percentile of average excess dryness experienced a 10% reduction in the value of agricultural output per decade. This sharp reduction suggests a limited scope for adaptation responses within the agricultural sector such as the adoption of new technologies or changes in crop composition.

Next, we study the direct and indirect effects of excess dryness on capital reallocation. We study both the effects of short-run weather shocks, measured as a yearly increase in excess dryness; and long-run climate change, measured as decadal increases in excess dryness. Our findings indicate that, in the short-run, the financial system favors risk sharing in regions affected by climate shocks with the support of financially connected regions. However, over the long-run, the evidence stands in sharp contrast with the predictions of classical open economy models. Those models predict that as persistent droughts 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. More specifically, a municipality moving from the median to the 90th percentile of average excess dryness experiences a 15 percent decadal decline in lending originated by local branches to all sectors of the economy. We also document negative indirect effects on municipalities that are financially integrated with areas experiencing excess dryness, leading to capital outflows. We find that in those indirectly affected regions, the contraction in credit hurts manufacturing employment. Thus, our findings suggest that persistent droughts not only reduce investment in agriculture, but also have negative spillovers on local non-agricultural sectors. In addition, they have negative spillovers on credit availability and industrial employment in other regions financially connected through bank branch networks.

Second, we study the direct and indirect effects of excess dryness on labor reallocation. We find that municipalities moving from the median to the 90th percentile of average dryness over the 2001-2010 period relative to the previous century experience a sharp reduction in employment in both agriculture (-6.9%) and services (-4.7%), but an increase in manufacturing employment (5.3%). These changes in the structure of the local economy are consistent with the predictions of our model, where a reduction in agricultural productivity shifts comparative advantage towards manufacturing but reduces demand for local non-traded goods such as services. Still, our estimates indicate that only a third of the workers displaced from agriculture and services are absorbed by local

manufacturing, leading to net out-migration from affected areas (driven by outflows). As a result, a municipality moving from the median to the 90th percentile of decadal excess dryness experiences a 4.9 percent reduction in population.

When studying indirect effects of excess dryness through labor markets, we find that more exposed municipalities experience a larger increase in net in-migration (driven by inflows) and expand employment in agriculture and services, but not in manufacturing. This is not consistent with our neoclassical model, which predicts that an inflow of labor reinforces the comparative advantage of manufacturing. This is because agriculture is intensive in the use of land, which is in fixed supply. Allocating more workers into agriculture would generate decreasing returns. Thus, the model predicts an expansion of manufacturing both in terms of labor and its complementary factor, capital. This mismatch between the neoclassical predictions of the model and the empirical findings 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.

We infer labor market frictions across regions using past bilateral labor flows. This interpretation is based on the predictions of economic geography models of labor flows across regions. For example Borusyak et al. (2023) show that bilateral migration flows are a function of bilateral migration costs. These costs could reflect transportation or other labor market frictions such as search and matching costs. We use social security data to provide for a firm-level measure of bilateral labor market frictions: the share of workers in each firm coming from each origin municipality during a baseline period. Next, we split the sample of potential origins by the median level of excess dryness during the following decade, which is as good as randomly assigned. If bilateral labor market frictions were symmetric across sectors, we should find that firms in agriculture, manufacturing and services have a similar share of workers coming from those origins. However, we find that firms in the manufacturing sector are less integrated with areas that would eventually become dryer. In the baseline period, only 2 percent of workers employed by manufacturing firms came from those areas compared to 4 percent in services and 6 percent in agriculture. This represents an asymmetry in bilateral labor market frictions across sectors that can potentially explain the mismatch between our findings and the predictions of our neoclassical model.

In the last part of the paper, we provide micro-based evidence on the indirect effects of excess dryness via migrant networks using employer-employee level data. This identification strategy exploits variation in flows of migrant workers from different origins to the same firm, and thus permits to control for firm-level shocks. We document that firms in the manufacturing sector display a lower elasticity of employment to labor supply shocks driven by climate migrants from connected origins. This implies that manufacturing firms are less prone to employ migrants pushed away by excess dryness. We argue that this

finding could be explained by the lower level of initial connections between manufacturing firms and regions getting drier described above. Indeed, in a counterfactual analysis, we show that equalizing the level of such connections across sectors fully closes the gap in the elasticity of employment to labor supply shocks between manufacturing, agriculture and services.

Finally, we discuss and address potential concerns with our empirical analysis. First, to account for spatial correlation in climatic conditions, we exclude from our measures of indirect effects the areas that are within a certain radius from a given municipality. We use a 55km radius in our baseline specification and show that results are robust to different thresholds. In addition, we show robustness to clustering standard errors at larger units of geographical aggregation above municipalities (e.g. meso-regions). Second, we recognize that excess dryness in some locations can have effects in other locations through channels other than labor and capital flows. For example, goods trade can generate demand or supply linkages across regions. To control for these linkages, we construct a measure of exposure to excess dryness via trade links in the spirit of the market access measure of Donaldson and Hornbeck (2016). Controlling for this exposure leaves our estimates of labor and capital market links unaffected.

Related Literature

This paper builds on the empirical literature studying the effects of both temporary weather shocks and persistent changes in temperature on economic outcomes, reviewed by Dell et al. (2014). We contribute to this literature by i) measuring capital flows in addition to labor flows, ii) estimating not only local effects but also spillover effects on destination regions, and iii) tracking climate migrants across regions, sectors and firms using social security data. Studying how climate change simultaneously affects labor and capital allocation both across regions and sectors paints a more comprehensive picture on the relative importance of potential adaptation mechanisms and how they are shaped by factor market integration.

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

More recently, the literature has focused on understanding spillover effects of regional

shocks building on the market access approach developed by Redding and Venables (2004) and Donaldson and Hornbeck (2016). Adao, Arkolakis, and Esposito (2019b) study direct and indirect effects of regional trade shocks in the US. Fajgelbaum et al. (2021) estimate the indirect effects through the trade network of the US-China trade war. In turn, Bustos, Garber, and Ponticelli (2020) study direct and indirect effects of agricultural productivity growth on capital flows from rural to urban areas in Brazil. Finally, in contemporaneous and independent work, Borusyak et al. (2023) show that empirical estimates of the effects of local labor demand shocks on population which do not take into account the shocks to potential destinations of migrants suffer from attenuation bias whenever shocks are spatially correlated. They propose an economic geography model leading to a specification that combines shocks across locations with information on pre-shock migration connections to capture the relative importance of each potential destination for a locality. They suggest to implement a first order approximation to this equation that corresponds to our empirical strategy to estimate spillovers through labor markets.

Empirical studies on the effects of weather shocks on labor markets show that they can generate migration away from affected areas (Jayachandran, 2006; Hornbeck, 2012).⁵ Some recent studies have focused on the impact of weather shocks on labor reallocation across sectors, and in particular on the ability of non-agricultural sectors to absorb displaced agricultural workers. For example, Colmer (2021) finds evidence that short-run weather shocks reduce agricultural productivity and generate worker reallocation from agriculture into both manufacturing and services within the same district, but no out-migration. In turn, Henderson et al. (2017) studies the negative impact of long-run changes in moisture on agricultural productivity in Sub Saharan Africa, documenting that only areas with an export-oriented manufacturing sector are able to absorb displaced agricultural workers.⁶ Overall, the literature has focused on the local labor market effects of climate shocks. We contribute to this literature by estimating the response of capital flows across sectors and regions using micro data on lending and deposits which, to the best of our knowledge, had not been previously studied. In addition, by tracking climate migrants across regions, we can provide direct empirical evidence on the spillover effects of local shocks into other regions integrated through labor markets.

A few empirical studies have focused on how market integration shapes the response of local economic outcomes to weather shocks. Jayachandran (2006) finds that wages fluctuate more in response to weather shocks in Indian districts with fewer banks or higher migration costs. Consistently, Burgess and Donaldson (2010) find that local rainfall shortages were less likely to cause famines in colonial India after railroad access increased

⁵However, Boustan et al. (2012, 2020) study the response to natural disasters in the U.S. and find in-migration in response to floods. Their analysis excludes drought events due to endogeneity concerns related to water management practices, as they use administrative data to measure natural disasters.

⁶See also McGuirk and Nunn (2020) on the effects of climate change on the timing of seasonal migration by pastoral groups in Sub Saharan Africa and ensuing conflicts with local farmers.

trade openness. More recently, Allen and Atkin (2022) show that expansions of the Indian highway network reduced the responsiveness of local prices to local rainfall but increased the responsiveness of local prices to yields elsewhere so that farmers shifted their production towards crops with less volatile yields. We contribute to this literature by i) showing how the effects of persistent changes in dryness can be different from those of temporary weather shocks, and ii) tracking spillovers to non-agricultural sectors and other regions by directly measuring labor and capital flows.

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

II CONCEPTUAL FRAMEWORK

Our empirical work provides direct estimates of (1) the effect of regional climate shocks on factor allocation across sectors in directly affected regions; (2) the magnitude and direction of the factor flows across regions generated by climate shocks; (3) the effects of those factor flows on structural transformation in destination regions. To interpret these 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 response of factor allocation 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.⁷ Then, we use the model to predict the effect of local agricultural productivity decline on local factor markets. We call these the direct effects of climate change.

⁷Note 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.

In addition, we study the spillover effects of climate change through factor flows across municipalities. This is motivated by our empirical finding that worsening climatic conditions generate labor and capital outflows from directly affected areas. We find that other regions integrated with affected areas through past migrant networks are the destination of these labor flows (section IV.C). In contrast, we find that areas financially integrated to affected areas suffer capital outflows (see section IV.B). Note that, as discussed above, we do not model factor flows across regions explicitly. Still, we can use the model to assess the indirect effects of climate change through labor and capital flows by treating these changes in factor supply as exogenous from the point of view of the destination region.

II.A MODEL SETUP

We present a classic small open economy model with two traded sectors, agriculture (a) and manufacturing (m) and one non-traded sector, services (s). There are three production factors in fixed supply within each region: land (T), capital (K) and labor (L).⁸ We assume that agricultural production uses the three factors, under constant returns to scale. In turn, manufacturing and services only use capital and labor. To simplify the analysis, we assume that all sectors use capital and labor in the same proportions. As a result, the model inherits the workings of a textbook Ricardo-Viner (or factor-specific) model as described by Dixit and Norman (1980).⁹

Goods and factor markets are perfectly competitive. 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:

$$U(c_a, c_m, c_s) = c_a^{\alpha_a} c_m^{\alpha_m} c_s^{\alpha_s},$$

with $\alpha_a + \alpha_m + \alpha_s = 1$. In turn, production functions in each sector are:

$$\begin{aligned} Q_a &= A_a T_a^\beta (K_a^\gamma L_a^{1-\gamma})^{1-\beta} \\ Q_m &= A_m K_m^\gamma L_m^{1-\gamma} \\ Q_s &= A_s K_s^\gamma L_s^{1-\gamma} \end{aligned}$$

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 $X = K^\gamma L^{1-\gamma}$.

⁸We omit region subindexes for simplicity

⁹For 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). We think that because climate change generates scarcity of productive land, 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.

II.B EQUILIBRIUM

In this section we describe the main features of equilibrium prices, factor rewards and sectoral employment shares, 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

We start by discussing the sectoral employment shares of the mobile factors, capital and labor. The equilibrium employment share in agriculture is increasing in its comparative advantage with respect to manufacturing. Comparative advantage 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 [$T/(K^\gamma L^{1-\gamma})$]. 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 aggregate demand for services is a constant share (α_s) of income from each of the three production factors ($wL + r_k K + r_T T$). Wages and the reward to capital are independent of agricultural productivity, as discussed above. In contrast, land rents are an increasing function of agricultural productivity because land is only used in the agricultural sector. As a consequence, the employment share in services is an increasing function of agricultural productivity. In addition, it is increasing in land abundance relative to the composite mobile factor [$T/(K^\gamma L^{1-\gamma})$]. This is because a larger land endowment increases income per capita and the demand for services. See Appendix equation (A10) for a formal solution of equilibrium employment shares in services.

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 start by analyzing the local effects of climate change in directly affected regions. 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*

As mentioned above, our empirical findings suggest that climate change can affect regions indirectly through factor reallocation across space in response to permanent agricultural productivity declines in directly affected regions. While our model does not feature factor flows, we can still use it to study their consequences for regions experiencing changes in factor supply due to spatial reallocation. In particular, we assume that there is a permanent change in the supply of labor (capital), which is exogenous from the point of view of the indirectly affected region. Then we use the model to predict the resulting changes in the equilibrium factor allocation across sectors.

Labor. We study the effects of an inflow of climate migrants on 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 manufacturing employment share of both factors must increase (see Appendix section A.B.2 for a proof).

Capital. Second, 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. This is because the reduction in capital supply implies that land abundance increases which reinforces the comparative advantage of agriculture. Thus, agricultural employment shares of both factors increases. Second, lower

capital income reduces the demand for services, but less than proportionally to the fall in capital supply. As a result, the employment share of the service sector for both factors increase. Finally, for the manufacturing sector, factor market equilibrium implies that employment shares of both factors fall. As the labor endowment is fixed, the changes in employment shares discussed above imply that labor flows into agriculture and services and flows out of manufacturing. (see Appendix section A.B.2 for a proof).

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 1850-1900.¹⁰

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 Proteção 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 2018.¹¹ Figure II 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.

Figure III shows the geographical distribution of reported droughts across Brazil in the 2000-2010 period (panel a) and 2011-2018 period (panel b). As shown, although droughts are reported all over the country, reports tend to be clustered in the inner region of

¹⁰For 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).

¹¹The objective of these reports is to provide the central government with an initial assessment of the damages and thus obtain financial and logistical support.

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.¹² Crucially for our purposes, SPEI measures standard *deviations* of dryness relative to the historical average observed in a given locality.¹³ 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, we show in Appendix B that 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.

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 panels (c) and (d) of Figure III, 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.

Importantly, changes in average dryness in the first decade of the 2000s relative to historical averages turn out to be uncorrelated with initial characteristics of municipalities, thus approximating the ideal of “as-good-as-randomly assigned” treatment. Panel B of Table II shows that there is no correlation between excess dryness during the 2001-2010 period and a set of baseline municipality characteristics.¹⁴ Instead, the frequency of

¹²Potential 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).

¹³SPEI 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.

¹⁴A potential additional concern with this measure is that changes in temperature and rainfall could be driven by deforestation and thus endogenous to agricultural development. However, we show that excess

reported droughts in the SINPDEC data tends to be higher in poorer municipalities, as shown in Panel A of Table II.¹⁵

Finally, Figure IV reports the distribution of $\Delta Dryness$ across Brazilian municipalities in the first and second decade of the 2000s. As shown, 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 II, which shows an increase in the frequency of droughts across Brazilian regions during the last ten years relative to the previous decade. Figure IV also reports the median (black line) and 90th percentile (red line) of the distributions of excess dryness across municipalities in each decade. All quantifications in the paper are computed for a municipality moving from the median to the 90th 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.

In the following sections, we present the two main specifications we estimate. The first is aimed to capture short-run responses to weather shocks, measured as yearly deviations of dryness from centennial averages. The second estimates longer-run responses to potential changes in climate, measured as decadal changes in excess dryness relative to centennial averages.

III.B YEARLY PANEL SPECIFICATION

We study the direct and indirect effects of yearly variation in excess dryness on outcomes with the following panel specification at municipality level:

$$y_{mt} = \alpha_m + \alpha_{rt} + \beta_1 \underbrace{\Delta Dryness_{mt}}_{\text{Direct effect}} + \sum_{f=L,K} \beta_2^n \underbrace{Exposure_{mt}^f}_{\text{Indirect effects}} + \Lambda_t X_{m,t=1991} + u_{mt} \quad (1)$$

Where m indexes municipalities, r indexes one of the five macro-region of Brazil, and t indexes years.¹⁶ Municipality fixed effects (α_m) account for time-invariant unobservable characteristics at the municipality level, while macro-region fixed effects interacted with year fixed effects (α_{rt}) capture any common shock at the macro-region level. $\Delta Dryness_{mt}$ captures changes in dryness relative to the level of dryness historically recorded in a given municipality between 1901 and 1999. This is defined using the climatological dryness

dryness is also uncorrelated with cumulative deforestation experienced between 2001 and 2010.

¹⁵In addition, the propensity to report droughts might be correlated with other municipality characteristics that also affect our outcomes of interest. For example, poorer municipalities with less developed infrastructures to deal with exceptionally dry conditions might be more prone to reporting.

¹⁶Since borders of municipalities changed over time, in this paper we use AMCs (minimum comparable areas) as our unit of observation. AMCs are defined by the Brazilian Statistical Institute as the smallest areas that are comparable over time. In what follows, we use the term municipalities to refer to AMCs. Brazil is divided into five macro-regions defined by the IBGE: North, Northeast, Central-West, South and Southeast.

index SPEI as described in section III.A. $Exposure_{mt}^f$ captures the exposure of a given municipality to the excess dryness experienced by municipalities other than m based on their degree of integration with m via capital or labor markets. The superscript $n = K, L$ indicates the type of market integration. We describe in detail the measures of market integration in section III.D. $X_{m,t=1991}$ are a set of baseline municipality-level controls observed in the 1991 Population Census – which pre-dates the period of our analysis – interacted with year fixed effects. We present these controls in Table II below.

The main identification assumption when estimating equation (1) is that year-to-year variation in excess dryness across municipalities is plausibly exogenous relative to the outcomes of interest. Because year-to-year changes in excess dryness are a function of year-to-year changes in temperature and rainfall experienced in each location, equation (1) is likely to satisfy the identification assumption. Standard errors in all specifications are clustered at the microregion level to account for spatial correlation across municipalities. Microregions are groups of adjacent municipalities with similar production and geographic characteristics proposed by the IBGE. Brazil is divided into 558 microregions, each composed of about 8 municipalities.

III.C LONG DIFFERENCES SPECIFICATION

We study the direct and indirect long-run effects of excess dryness on factor allocation and flows by estimating the following differences-in-differences specification:

$$\begin{aligned} \Delta y_{m,2000-2010} &= \alpha_r + \beta_1 \underbrace{\Delta Dryness_{m,2001-2010}}_{\text{Direct effect}} \\ &+ \sum_{f=L,K} \beta_2^n \underbrace{Exposure_{m,2001-2010}^f}_{\text{Indirect effects}} + \Lambda X_{m,t=1991} + \varepsilon_m \end{aligned} \quad (2)$$

The outcome variable $\Delta y_{m,2000-2010}$ captures decadal variation in the outcomes of interest at municipality level between 2000 and 2010. We focus on these two years because of the timing of the Brazilian Population Census. $\Delta Dryness_{m,2001-2010}$ 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. As in equation (1), $Exposure_{m,2001-2010}^f$ captures the exposure of a given municipality to the excess dryness experienced over the same decade by municipalities integrated with m via capital and labor markets.

Equation (2) is similar to the long differences approach described in Burke and Emerick (2016), in which long-run changes in outcomes are regressed on long-run changes in temperatures. The key identifying assumption in this approach is that differential changes in dryness between the first decade of the 2000s and the previous century are uncorrelated

with other local shocks that might also affect the outcomes of interest. In what follows we provide evidence consistent with this assumption.

A first concern is that regions subject to increases in dryness also differ in geographical characteristics that determine their initial level of development and growth prospects, so that the parallel trends assumption is not satisfied. For example, they could be initially more arid and less developed. However, as discussed above, Panel B of Table II shows that there is no correlation between excess dryness during the 2001-2010 period and a set of baseline municipality characteristics reflecting the level of development. A second concern is reverse causality: changes in local economic activity might affect local climate. For example, there is evidence in natural sciences that changes in land use – such as the conversion of forest to pasture or cultivated agricultural land – can affect local climate (Spracklen et al., 2018; Lawrence and Vandecar, 2015). This concern is particularly relevant for Brazil, which experienced a vast increase in cropland in the first decade of the 2000s, often at the expense of pasture land and forest. This, in turn, might have contributed to lower rainfall and higher dryness (Araujo, 2023). However, excess dryness is uncorrelated with deforestation of the Amazon rain forest during the period under study (Panel B of Table II). In addition, in the empirical analysis, we control for measures of technical change in soy and maize – the main crops farmed in Brazil and those that experienced significant technological improvements during the period under study. Soy and maize technical change are defined as the theoretical increases in potential yields of these two crops obtained by switching from traditional to advanced agricultural techniques as described in (Bustos et al., 2016).

A third concern with our identification strategy is spatial correlation. In Figure III, we report the geographical distribution of $\Delta Dryness$ across Brazil in the 2001-2010 decade and the 2011-2018 decade. Although excess dryness tends to be less geographically clustered in certain areas of the country relative to reported droughts, the map shows how excess dryness is spatially correlated across municipalities. Thus, one concern is that most of the variation in excess dryness could be across Brazilian macroregions, e.g. because Northern Brazil is on average becoming drier at a faster pace than Southern Brazil. We take several steps in the empirical analysis to account for spatial correlation. First, we show that results are robust to absorbing macroregion specific trends, as shown in equations (1) and (2). This implies that there is still large residual variation in excess dryness after accounting for common trends in each macroregion of the country. Second, we show in the Appendix that estimates are robust to clustering standard errors at higher levels of geographical aggregation than macroregions, namely mesoregions (115 regions). Third, we control and estimate the indirect effects of excess dryness on connected regions both through labor and capital markets. This is key to deal with spatial correlation as argued by Borusyak et al. (2023) in the context of labor market links across regions. They show that empirical estimates of the effects of local labor demand shocks on population which

do not take into account the shocks to potential destinations of migrants suffer from attenuation bias whenever shocks are spatially correlated. In the next subsection, we detail how we measure these indirect factor market links across locations.

III.D MEASURES OF INDIRECT EXPOSURE TO EXCESS DRYNESS

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

To capture the indirect effects of excess dryness on regions connected via capital markets, we construct a measure of municipality-level exposure via bank branch networks. This measure 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. We construct the measure in two steps. First, we define the degree of exposure of each bank to changes in excess dryness based on the geographical structure of its initial bank branch network as follows:

$$BankExposure_{bt} = \sum_{o \in O_b} \omega_{bo} \Delta Dryness_{ot}, \quad (3)$$

where the weights ω_{bo} are the share of national deposits of bank b coming from origin municipality o in the baseline year 2000, and O_b is the set of origin municipalities in which bank b was present in 2000.

Next, we define the municipality-level exposure to excess dryness via bank branch networks as follows:

$$Exposure_{mt}^K = \sum_{b \in B_m} w_{bm} BankExposure_{bt}, \quad (4)$$

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

Consistent estimation of the indirect effects of excess dryness via bank branch networks described in equation (4) relies on identification assumptions that are similar to the ones of a shift-share instrumental variable regression. Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020) discuss conditions for consistent estimation in shift-share research designs that combine a set of shocks with exposure shares. Our setting most closely matches the framework described in Borusyak et al. (2022), where identification relies on

shocks that are as-good-as-randomly assigned across locations but variation in exposure shares can be endogenous.¹⁷ As shown in section III.A, changes in excess dryness in origin municipalities are only determined by changes in temperature and rainfall during the 2001-2010 period relative to historical averages, and are uncorrelated with baseline municipality characteristics. We think of this as plausibly exogenous shocks. On the other hand, the levels of exposure shares – the weights in equations (3) and (4) – are likely to be endogenous to municipality characteristics. We construct time-invariant weights using data on bank branch locations that predate the period under study, in order to ensure that variation in weights does not capture endogenous changes in the number of bank branches – due to openings of new branches or closings of existing ones – during the 2001 to 2010 period.

III.D.2 Exposure via labor market integration

To estimate the indirect effects of excess dryness on regions integrated through labor markets, we construct a measure of labor market integration across municipalities using data from past migration flows. The classic justification for this measure of labor market integration is that migrants tend to choose destinations that were previously chosen by migrants from their same origin region because social networks reduce migration costs (Altonji and Card, 1991; Card, 2001). For example, former migrants from the same origin might offer labor market referrals that reduce job search costs.

The Brazilian Census allows us to construct internal migration flows based on a question asking respondents for their municipality of residence five years prior to the Census year. Thus, using the 2000 Census, we calculate bilateral migration flows between each pair of municipalities during the period 1995-2000. We then construct the exposure to changes in excess dryness via migration links as

$$Exposure_{mt}^L = \sum_{o \neq m} \alpha_{om} \Delta Dryness_{ot},$$

with

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

where o denotes the origin municipality, m the destination municipality, $M_{1995-2000,o \rightarrow m}$ the size of the migrant flow from o to m between 1995 and 2000, and $M_{m,2000}$ the total number of individuals that migrated during this period to m . Recently, Borusyak et al. (2023) show that this expression for the spillover effects of regional shocks can be derived from a theoretical model of a small open economy with endogenous worker location de-

¹⁷In particular, Borusyak et al. (2022) show that a shift-share IV strategy leads to consistent estimates under i) quasi-random shock assignment and ii) many uncorrelated shocks. The latter implies that the number of shock observations grows with sample size, which is the case in our setting where shocks are observed at the municipality level.

cisions. In their setup, lower baseline migration flows across municipalities reflect larger bilateral migration costs. Importantly, they show that consistent reduced-form estimation of the indirect effects requires that migrant flows are measured in a previous period and shocks are as-good-as-randomly assigned. The first requirement is satisfied by our measure of migration flows as we use data from the previous Population Census to measure them. The second assumption is supported by the fact that variation in excess dryness is driven by changes in temperature and rainfall which are plausibly exogenous and uncorrelated with baseline municipality characteristics, as discussed above (Panel B of Table II).

III.D.3 Separately identifying direct and indirect effects

There are two key empirical challenges that researchers face when attempting to separately identify the direct and indirect effects of local shocks. The first is that shocks might be spatially correlated. The second is that the different types of connections across regions through which indirect effects percolate – for example, migrant networks and capital networks – might be themselves geographically correlated across markets. We discuss these two challenges below.

First, direct and indirect effects might be difficult to separate when shocks are spatially correlated. Our strategy to deal with this concern is using economic theory and detailed data that permits to assess whether we can empirically separate direct and indirect effects through labor and capital markets. For example, when we look at migration flows, we show that the direct effect of dryness is to generate labor outflows from directly affected regions and labor inflows into indirectly affected regions. This is exactly what we would expect in classic migration models with regional income shocks (Kennan and Walker, 2011).

In addition, when we investigate the indirect effect of excess dryness on connected regions, we exclude from our measures of exposure areas that are within a 55km radius from a given municipality. This is because the SPEI dataset is a grid with spatial resolution of 0.5° ($55\text{km} \times 55\text{km}$). Thus, this exclusion insures that our measures of indirect exposure do not capture the effect of dryness recorded in other municipalities located within the same SPEI grid cell. All our results are quantitatively similar if we remove this adjustment or we use an alternative measure of exposure excluding areas within a larger 111km radius (1°) from each municipality, as shown in the Appendix of the paper. Indeed, we document that estimates become less noisy as we keep removing nearby locations from the measures of indirect exposure. This is consistent with the fact that this spatial adjustment lowers the correlation between direct and indirect measures of exposure to excess dryness, allowing us to better separate direct and indirect effects.

The second concern is that labor and capital market integration across municipalities could be driven by common geographical factors, which would make it hard to separately

estimate the indirect effects through each market. This is not the case in our setting. As shown in Table C1, the correlation between the measures of indirect exposure via labor and capital markets is low (0.157), suggesting that the two measures capture different networks. This might be due to the fact that bank branch networks are based on common ownership by the same bank, and less dependent on physical distance and other geographic factors influencing transport costs which are instead key in determining bilateral migration costs.

A related concern is that transport costs not only affect migration costs but also goods trade costs. Thus, our measure of indirect effects through labor market integration could be capturing spillovers through goods markets. For example, increases in dryness could reduce demand for goods produced in other regions, or the supply of inputs used in other regions, generating a negative spillover effect on labor demand. For this reason, when studying labor market outcomes we control for a market access measure in the spirit of Donaldson and Hornbeck (2016). In particular, we adapt the empirical strategy to estimate indirect effects of regional trade shocks derived from an economic geography model by Adao et al. (2019a). We define indirect goods market exposure as $\sum_{o \neq m} \tau_{om}^{-\theta} \Delta Dryness_{ot}$, where τ_{om} is the trade cost between municipalities o and m , and θ is the trade elasticity and $\Delta Dryness_{ot}$ is our measure of the regional shock.¹⁸

Our results below indicate that the indirect goods market exposure measure has no additional explanatory power over the labor and capital market indirect exposure measures. This finding suggests that our measure of indirect labor market links is not capturing goods market links. However, let us note that it is not obvious ex ante that our measure of exposure via goods market is an appropriate control variable. This is because we do not directly observe trade flows across municipalities, and thus need to rely on the theoretical market access measure where goods market links are a function of traveling costs. This raises two issues. First, in economic geography models, bilateral labor flows are also a function of bilateral travel costs, thus we could be “over-controlling”. Second, if there are additional bilateral frictions common to goods and labor markets, our measure of labor market links could also be capturing goods market links. To address this concern, we implement a version of our empirical strategy to estimate labor market links that exploits variation at the time-firm-origin-level and thus permits to control for firm-level shocks. Under the assumption that goods market connections affect product demand or input supply at the firm-level, this strategy permits to separate indirect labor and goods market effects. We describe it in detail below.

¹⁸The trade cost is based on the bilateral traveling cost via the Brazilian highway network in the year 2000 following Astorga (2019). The traveling costs c_{om} are obtained by dividing Brazil in grid cells and applying the fast marching method algorithm to determine the most efficient route between each pair of municipalities under the assumption that crossing a cell without a federal highway has a traveling cost 3.5 times higher than one with a federal highway. As in Allen and Arkolakis (2014), we then compute trade cost as the exponential form $\tau_{om} = \exp(c_{om})$. For the trade elasticity θ , we use the estimate of 3.39 by Astorga (2019).

III.D.4 Estimating indirect effects using employer-employee data

To fully disentangle the indirect effects of excess dryness via labor market connections from other mechanisms, we propose an identification strategy that exploits variation in flows of migrant workers across firms located in the same municipality using the employer-employee dataset RAIS. RAIS contains information on all formal workers in Brazil, allowing us to follow each worker over time across firms, sectors and locations.¹⁹

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:

$$\alpha_{oi(m),t^*} = \frac{L_{i(m),t^*,o \rightarrow d}}{L_{i(m),t^*}} \quad (5)$$

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 (5) 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.D.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:

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

The outcome variable in equation (6) 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

¹⁹Employers are required by law to provide detailed worker information to the Ministry of Labor. See Decree n. 76.900, December 23rd 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)

that occurred in the origin between 2006 and 2010. To make estimation computationally less intensive, we aggregate all potential origin municipalities in two groups: origins that experienced very high excess dryness during the 2006-2010 period, which we define as those in the top quartile of $\Delta Dryness$, 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 (6) 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.²⁰ When estimating equation (6) 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

In this section, we present the main results on the effects of excess dryness on the local economy of the affected regions and on the economy of regions integrated with the affected regions via capital and labor markets. We then compare our empirical findings with the predictions of the benchmark open economy model without frictions presented in section II.

We start in section IV.A by analyzing the effect of excess dryness on local agricultural production. Next, in sections IV.B and IV.C, we study how excess dryness affects capital and labor allocation across sectors in areas that are directly or indirectly affected by such shocks.

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 logs). 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 it is designed to be 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,

²⁰Since we aggregate origins in two groups, the dummy $1(Dry)_o$ effectively captures the origin fixed effect.

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.

We start by estimating the panel regression described in equation (1) over the time period 2000-2018. We do not include controls for indirect factor market effects in this specification as we attempt to capture how dryness affects the productivity of land, an immobile factor. The results are reported in Panel A of Table III. The magnitude of the coefficients reflects the effect of an increase in excess dryness from the median to the 90th percentile of the distribution of $\Delta Dryness$. Columns (1) and (3) show that a municipality moving from the median to the 90th percentile experiences an 8 percent decline in both area farmed and value of agricultural production. Columns (2) and (4) show that the magnitude of the documented effect is stable when including municipality controls interacted with year fixed effects. Overall, these estimates indicate that excess dryness relative to usual meteorological conditions causes sizable output losses in the agricultural sector.

We also document that the reduction in agricultural output is non-linear in the level of excess dryness. Figure V shows that municipalities in the top decile of the distribution of excess dryness suffer a loss of 16 percent in the value of agricultural production relative to those in the middle of the distribution, while municipalities in the bottom decile experience no significant change. This indicates that while extremely dry conditions – which are driven by higher temperatures and lower rainfall – relative to historical averages are detrimental for agricultural production, lower temperatures and higher rainfall have on average non-significant effects.

Next, in panel B of Table III, we estimate equation (2) to study the long-run effects of average excess dryness relative to historical averages. The outcome variable in this specification 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 more than 20% in the last two decades. Long-run declines in agricultural area and value of production that are of similar or even larger magnitude than those observed in the yearly panel specification reported in Panel A suggest limited adaptation responses to climate change by the agricultural sector.

IV.B THE EFFECTS OF EXCESS DRYNESS ON CAPITAL ALLOCATION

Yearly panel specification. We start by documenting the short-run effects of excess dryness on capital by estimating equation (1) using three main outcomes: loans, deposits and net capital flows. Data on loans and deposits is sourced from the ESTBAN dataset of the Central Bank of Brazil. ESTBAN reports balance sheet information at branch level for all commercial banks operating in the country. Loans and deposits are assigned to municipalities based on the location of the branch that originated the loan or received the deposit. For regulatory reasons, loans to the agricultural sector are recorded separately from total loans, which allows us to study the effect on agriculture vs non-agricultural lending separately.²¹ Net capital flows are constructed as loans originated by local bank branches minus deposits in those same branches, normalized by assets. Thus, a positive change in net capital flows indicates that local bank branches experience an increase in lending that is larger than the increase in local deposits, implying that the municipality is a net importer of capital. On the other hand, a negative change in net capital flows indicates that the municipality is exporting capital to other regions.

The main results for the year-to-year effect of excess dryness on capital outcomes are summarized in Figure VI (a) and (b), and reported in detail in Table IV. The key result is that, in the short-run, regions suffering abnormally dry conditions experience an increase in agricultural loans financed by capital inflows [Figure VI (a)]. In turn, regions indirectly connected through the bank network to areas suffering droughts experience capital outflows and a reduction in loans [Figure VI (b)]. Overall, this suggest that regions with abnormally dry conditions insure themselves in the short-run against negative weather shocks by importing capital via the banking sector, while connected regions provide insurance through funding the increase in lending to agriculture in affected regions and are therefore net exporters of capital. This is consistent with a consumption smoothing motive whereby individuals and firms operating in agriculture perceive the negative weather shocks as generating a temporary reduction in farm income, and thus borrow against their future income.

The magnitude of the coefficients reported in column (4) of Table IV implies that a municipality moving from the median to the 90th percentile of excess dryness experiences a 7.1 percent larger increase in loans to agriculture. This leads to an about 4 percent larger increase in total lending. In support of the identification assumptions, columns (1) to (3) show that the magnitude of the estimated direct effects remains stable when including indirect effects of exposure to dryness via banks in column (2) and municipality level controls interacted with year fixed effects in column (3). Notice also that connected regions that provide capital to directly affected regions experience a decline in overall

²¹Loans 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.

lending, which is concentrated in agricultural loans.²²

The magnitude of the estimated coefficient on the direct effect of excess dryness on net capital flows indicates that a municipality moving from the median to the 90th percentile of excess dryness experiences a 1.35 percentage points larger net *inflow* of capital as a share of assets of local bank branches. A municipality moving from the median to the 90th percentile of exposure to dryness via banks experiences net *outflows* of capital of about 1.6 percentage points. Finally, we find no significant direct or indirect effects on local deposits. This suggests that the direct effects on loans are not being driven by underlying trends in the local availability of capital through deposits.

Long-run differences specification. Next, we study the long-run effects of direct and indirect exposure to excess dryness by estimating equation (2) where the outcome variables are long-run changes in loans, deposits, and net capital flows at municipality level between 2000 and 2010. We focus on this decade to match the analysis on labor reallocation using the Population Census years presented in section IV.C.

The results are summarized in Figure VI (c) and (d) and reported in detail in Table V. The key findings are that, in the long-run, excess dryness generates lower lending in both directly affected and indirectly affected regions. A municipality moving from the median to the 90th percentile of average excess dryness over the 2001 to 2010 period experienced a 16 percent decline in the balance of outstanding loans originated by local branches. This result is robust to adding measures of indirect exposure via banks and migrant networks, as well as municipality level controls, as shown in columns (2) and (3). In turn, we do not find a significant change in deposits, which together with the reduction in loans implies capital outflows from regions directly affected by persistent increases in dryness. Note that this result is exactly the opposite of the short-run-insurance result documented above, where regions suffering droughts were net recipients of capital. In turn, the indirect effect estimates show that regions exposed to excess dryness via banks experience a significant decline in total lending. The magnitude of the effect is about half the size of the direct effect, and precisely estimated. Finally, let us note that the reduction in loans both in directly and indirectly affected regions is driven by both lower loans to agriculture and other sectors.

To interpret these findings, we use the benchmark neoclassical model presented in section II and its predictions summarized in Table I. First, for directly affected regions, the model predicts that a reduction in agricultural productivity reallocates capital away

²²Notice that magnitudes of direct and indirect effects are not directly comparable as the level of agricultural lending differ between municipalities providing capital and those that receive it. A potential explanation for the decline in agricultural lending in indirectly affected regions is that Brazilian financial institutions are required to allocate 25% of unremunerated deposits (i.e. deposits in checking accounts) to agricultural loans. This constraint is binding for most banks, which would rather allocate less than the target threshold to the agricultural sector. When such banks experience an increase in lending demand in affected areas, they might compensate by decreasing their loan origination in non-affected areas so to keep their overall exposure to the agricultural sector at the mandated minimum.

from 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. First, 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. On the contrary, we observe capital outflows from those regions. Then, a neoclassical framework can not fully explain our empirical findings.

A plausible explanation for the finding that capital flows out of both directly and indirectly affected regions is the following. Recall that regions financially connected to areas experiencing droughts were providing insurance in the short-run through bank loans. 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.²³ If there are frictions in the interbank market, those banks might reduce lending everywhere, including branches located in regions not affected by excess dryness.²⁴

This credit disruption channel generates 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 in 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 and indirectly affected regions documented in Table V. It is also consistent with the findings documented in Table VIII 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 due to climate change. In the short-run, the financial system favors risk sharing in regions affected by weather shocks with the support of financially connected regions. However, over the long-run, the 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

²³See 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.

²⁴The 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.

towards local manufacturing or other regions. However, we find capital reallocation away from both local agriculture and non-agriculture. In addition, we find capital outflows from both regions affected by persistent increases in dryness and financially connected regions. Thus, our findings suggest that persistent increases in dryness not only reduce investment in agriculture, but also have negative spillovers on local non-agricultural sectors. In addition, they have negative spillovers on credit availability in other regions financially connected through bank branch networks.

IV.C THE EFFECTS OF EXCESS DRYNESS ON LABOR ALLOCATION

Employment. We first study the direct and indirect effects of excess dryness on the change in total employment between 2000 and 2010. Total employment is sourced from the Population Census, which is carried out by the IBGE at 10 year intervals. 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 results are reported in Table VI. In the specification in the first column, which includes the direct effect only, we obtain a negative employment effect of 1.2 percent in a region moving from the median to the 90th percentile of excess dryness. When including our measure of indirect exposure via migrants, this effects doubles to 2.5 percent, indicating the presence of a strong attenuation bias when not taking into account spillovers, as suggested by Borusyak et al. (2023). Our estimate of the indirect effect indicates that a municipality at the 90th percentile of exposure to dryness via migrants experiences a 2.2 percent increase in total employment relative to one at the median. Adding the full set of additional municipality-level controls to the regression in column (3) and the exposure to dryness via banks in column (4) leads to only minor changes in these estimates.

Contrary to regions connected via migrants, regions connected via the bank network experience a *negative* employment effect, which is around half as large as the direct effect. This finding is consistent with the net outflow of capital from connected regions documented in Table V. Thus, we find that exposure to excess dryness via the banking sector leads to a reallocation of both capital and labor. We discuss the effects on labor in more detail below when decomposing it by sector. In the last column of Table VI, we include an additional measure for indirect exposure to excess dryness, which is based on connections to other municipalities via travel distance in the spirit of the market access measure of Donaldson and Hornbeck (2016) as described in section III.D.3. Estimates remain virtually unchanged and its coefficient is small and insignificant.²⁵

²⁵We report direct and indirect effects of excess dryness on average wages in Appendix Table C2, finding small and insignificant estimates. A potential explanation is that the negative agricultural productivity shock caused by excess dryness – which we would expect to negatively affect wages – is accompanied by a change in the composition of the local labor force, whereby the former agricultural and services workers migrating out of affected regions were those earnings relatively lower wages at baseline.

Migration. We shed light on the mechanisms behind the results on employment by investigating the direct and indirect effects of excess dryness on migration flows across municipalities. Census respondents report information on their municipality of residence five years prior to the 2010 Census year. We use this information to construct bilateral migration flows across each municipality pair between 2005 to 2010, and then sum up these flows by destination and origin to obtain aggregate outflows and inflows for each municipality. We compute the rate of net migrant flows as:

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

An increase in *netflows* corresponds to an increase in net migration *into* a given municipality, while a decline in this variable corresponds to an increase in net migration *out* of a given municipality.

The key findings on migration flow rates are summarized in Figure VII, while detailed regression results are reported in Table VII. The main takeaways from the figure are that excess dryness generates net outflows of migrants from directly affected municipalities and net inflows of migrants into indirectly affected ones. More specifically, a municipality moving from the median to the 90th percentile of excess dryness experiences a 1.30 percentage points larger net outflow of migrants as a share of its population. On the other hand, a municipality moving from the median to the 90th percentile of indirect exposure to excess dryness via pre-existing migration networks experiences a 0.76 percentage points larger net inflow rate of migrants.²⁶

In the same figure, we decompose net migration flows into outflows and inflows. The negative direct effects are mainly driven by an increase in outflows of migrants from affected regions, while the positive indirect effects are mainly driven by an increase in inflows of migrants into connected regions. Overall, these results indicate that one important mechanism behind the employment results documented above is that excess dryness generates a spatial reallocation of workers from directly affected regions to regions that are connected via pre-existing migration networks.²⁷

Exposure via banks has no explaining power on net migration flows. This is because

²⁶Figure C1 shows how our estimates of direct and indirect effects of dryness on net migration flows change when we do not exclude areas within a 55km radius, and when we exclude larger areas around each municipality. Both direct and indirect effects are very stable in terms of magnitude and become less noisy when removing nearby locations from the measures of indirect exposure. This is consistent with the fact that this spatial adjustment lowers the correlation between direct and indirect measures of exposure to excess dryness.

²⁷Consistent with the documented effects on net migration flows, Table C2 shows that regions directly affected by excess dryness experience a relative decline in population, while regions indirectly affected via the migrant network experience a relative increase in population. Column (2) shows that the positive indirect effect of exposure to excess dryness via the migrant network is partially mitigated by the negative indirect effect of exposure via the bank branch network, which is consistent with our findings on lending and employment discussed above.

both outflows and inflows are lower in municipalities with higher exposure to dryness via banks, as can be seen in columns (4) and (5). A possible interpretation of this finding is that the outflow of capital from a region reduces its attractiveness for immigrants by harming its economy on the one hand, and hinders (potentially costly) outmigration by exacerbating financial frictions on the other hand.

Sectoral Structure of the Economy. 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.

The results on the direct and indirect effects of excess dryness on the allocation of labor across sectors are summarized in Figure VIII and reported in detail in Table VIII. 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 6.9 percent larger decline in agricultural employment between 2000 and 2010 than those at the median. Services also experience a significant decline of 4.7 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 above – or remain unemployed locally. Recall that Census data includes both formal and informal labor, and therefore any reallocation across sectors that also entails a reallocation to or from informality is captured in the estimates of Table VIII.

Focusing on the indirect effects, we find that regions more exposed to climate migrants expand employment in all sectors with the exception of manufacturing. More specifically, relative to those at the median, municipalities at the 90th percentile of exposure to excess dryness via the migrant network experience increases of 3.3 and 2.2 percent in agriculture and services, respectively, while the effect for manufacturing employment is small and not statistically significant. This implies a decline in the share of manufacturing employment in regions indirectly exposed to excess dryness via migration. 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 frictions in the allocation of labor displaced by excess dryness. We investigate this point using employer-employee data in what follows.

We also test for the indirect effects of exposure to labor flows from affected regions on capital allocation across sectors. The benchmark model presented in section II predicts that an increase in labor via will generate a decline in capital in agriculture and services,

and an increase in capital in manufacturing (second row of Table I). Columns (4) and (5) show results that are partly consistent with this prediction, with a positive and significant effect of exposure to dryness via migrants on lending to non-agricultural activities.

Indirect effects via migrant networks 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.D.4, 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 (6) – $\alpha_{oi(m)} \times 1(Dry)_o$ –, 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 IX 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.²⁸

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 C3, 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

²⁸A potential concern with the stylized fact presented in Figure IX (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 C2, 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 C2 shows that the stylized fact presented in Figure IX (a) applies to both formal and informal workers.

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 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 C4, 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 IX reports the results of estimating equation (6). 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 (6) with origin fixed effects, destination municipality fixed effects and our measure of exposure to migrants from a given region as explanatory variables. The estimated coefficient β_1 indicates that, in the 2006-2010 period, firms receive larger flows of migrant workers from regions with which they were initially more connected. The magnitude of the coefficient indicates that firms with a 10 percent larger initial connection to a certain origin municipality experience a 6 percent larger flow of workers from that region. This magnitude describes the increase in flows relative to other firms operating in the same destination municipality.

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

Even within a given destination municipality, firms more connected to areas with higher excess dryness via past migrant workers might be more connected to those areas also via trade networks or financial links. If that is the case, then the coefficient β_2 cannot be interpreted as capturing the indirect effect of excess dryness on firms' employment via labor reallocation. Thus, in column (3), we estimate equation (6) 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 IX, 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.²⁹ 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. We find that smaller firms tend to have larger elasticities of workers' flows from climate change exposed regions. In particular, firms with less than 10 employees (micro firms) with average connection to areas with high excess dryness experience a 1.3 percent larger flow of workers from such regions. This elasticity is 1.1 percent for medium-sized firms, and 0.7 percent for large 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 2005a, 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). Sec-

²⁹We compute this effect by multiplying the estimated coefficient β_2 in column (4) of Table IX by the average connection of agricultural firms to Dry origins.

ond, 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.³⁰

V CONCLUDING REMARKS

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

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

Regions receiving climate migrants expand employment in agriculture and services, but not in manufacturing. Using social security data, we provide evidence that labor market frictions direct migrants to firms connected to migrants' social networks, which are mostly disconnected from manufacturing firms at destination. This force generates de-industrialization and increases the weight of small firms in the firm size distribution of destination regions.

³⁰See Lucas (1978); Melitz (2003) for classic models of the firm in which more productive firms tend to be larger. Empirically, see Syverson (2004) for a discussion of the correlation between firm size and quantity based measures of total factor productivity.

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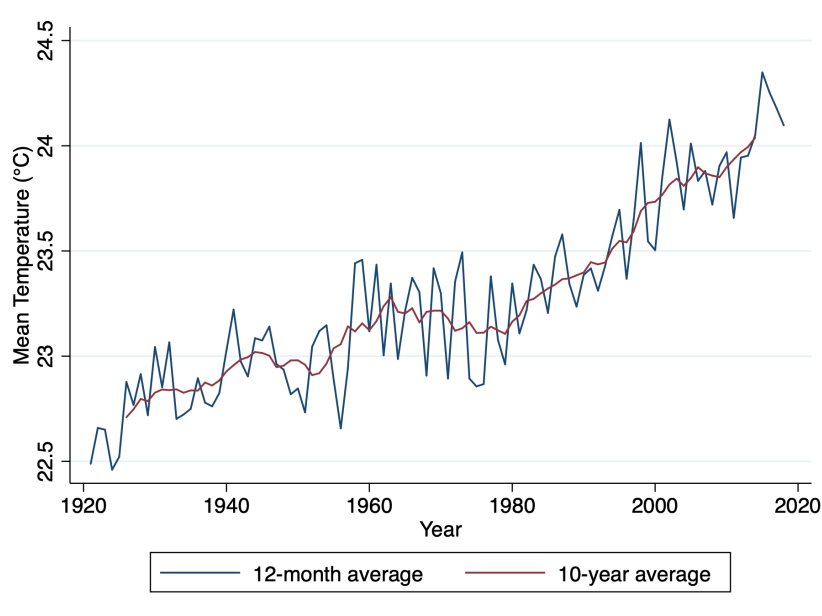
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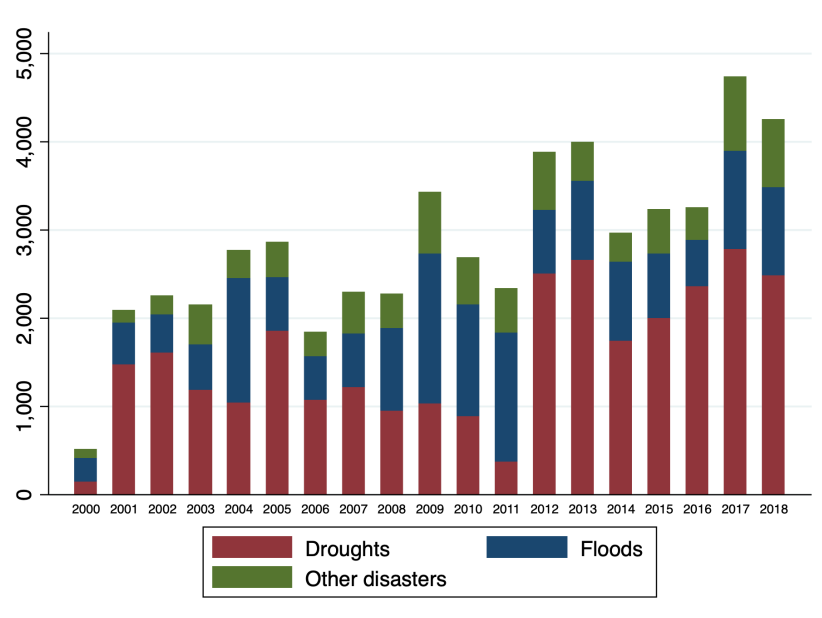
FIGURES

FIGURE I: AVERAGE TEMPERATURE IN BRAZIL SINCE 1920



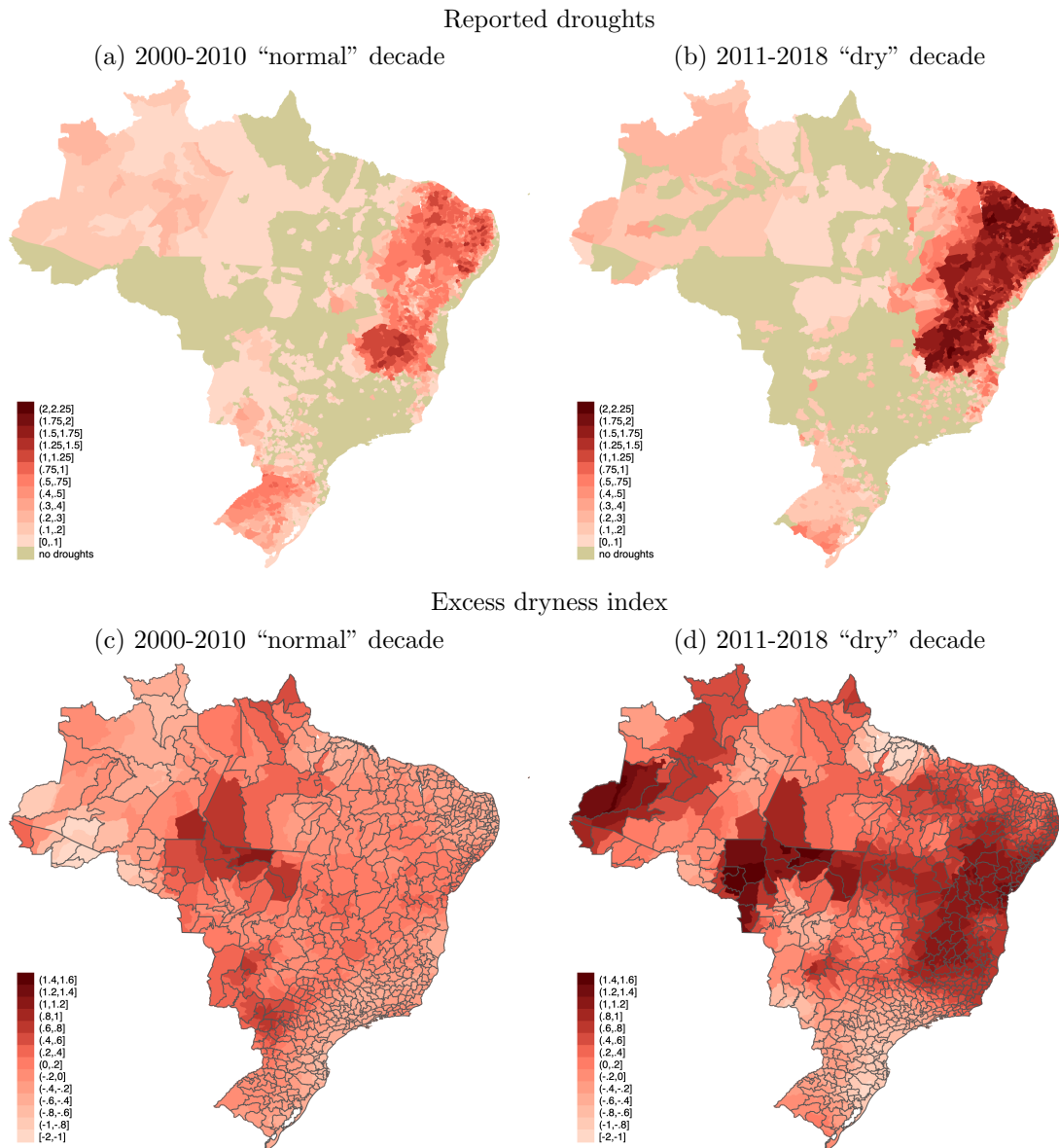
Source: Climatic Research Unit, University of East Anglia.

FIGURE II: REPORTED NATURAL DISASTERS BY YEAR: 2000-2018



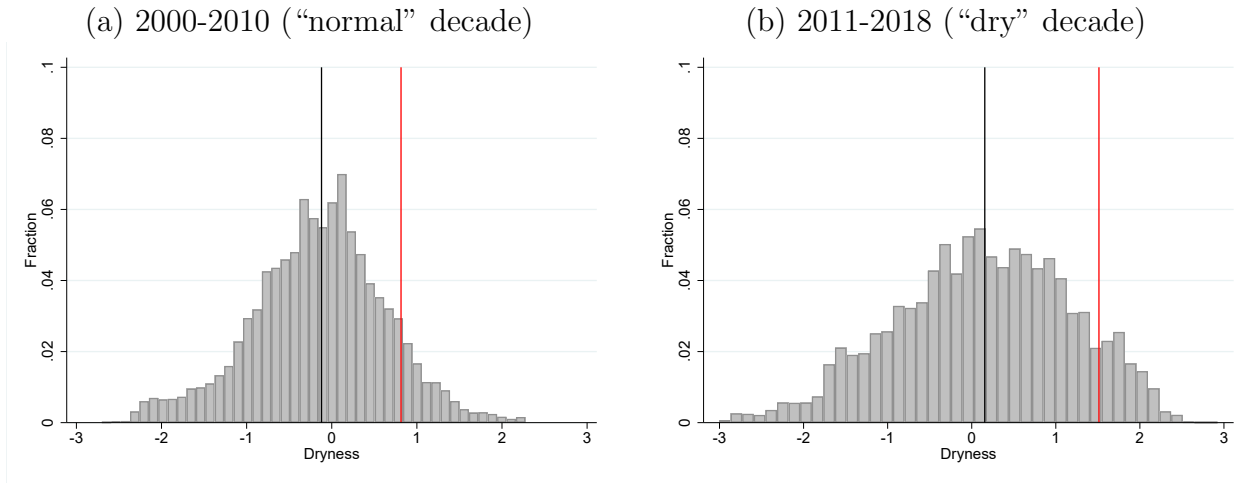
Source: Sistema Nacional de Proteção e Defesa Civil - SINPDEC

FIGURE III: GEOGRAPHICAL DISTRIBUTION OF REPORTED DROUGHTS AND SPEI



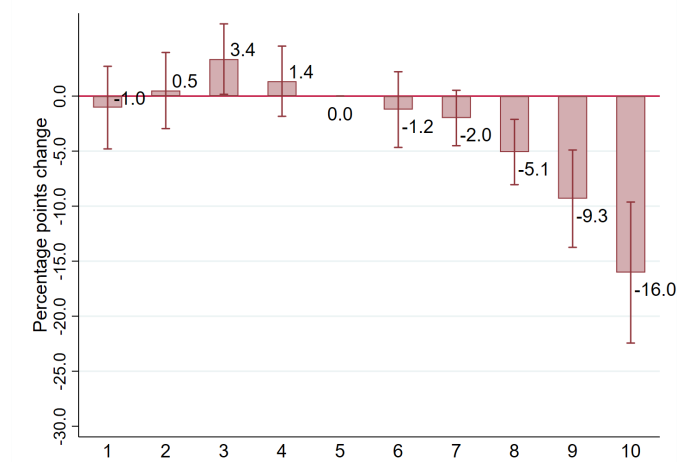
Notes: Maps (a) and (b) show the average number of reported droughts per year during the indicated time period. Maps (c) and (d) show the excess dryness index (average SPEI multiplied by -1) during the indicated time period as well as the borders of the 558 microregions of Brazil, the level of clustering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

FIGURE IV: DISTRIBUTION OF EXCESS DRYNESS INDEX ACROSS MUNICIPALITIES



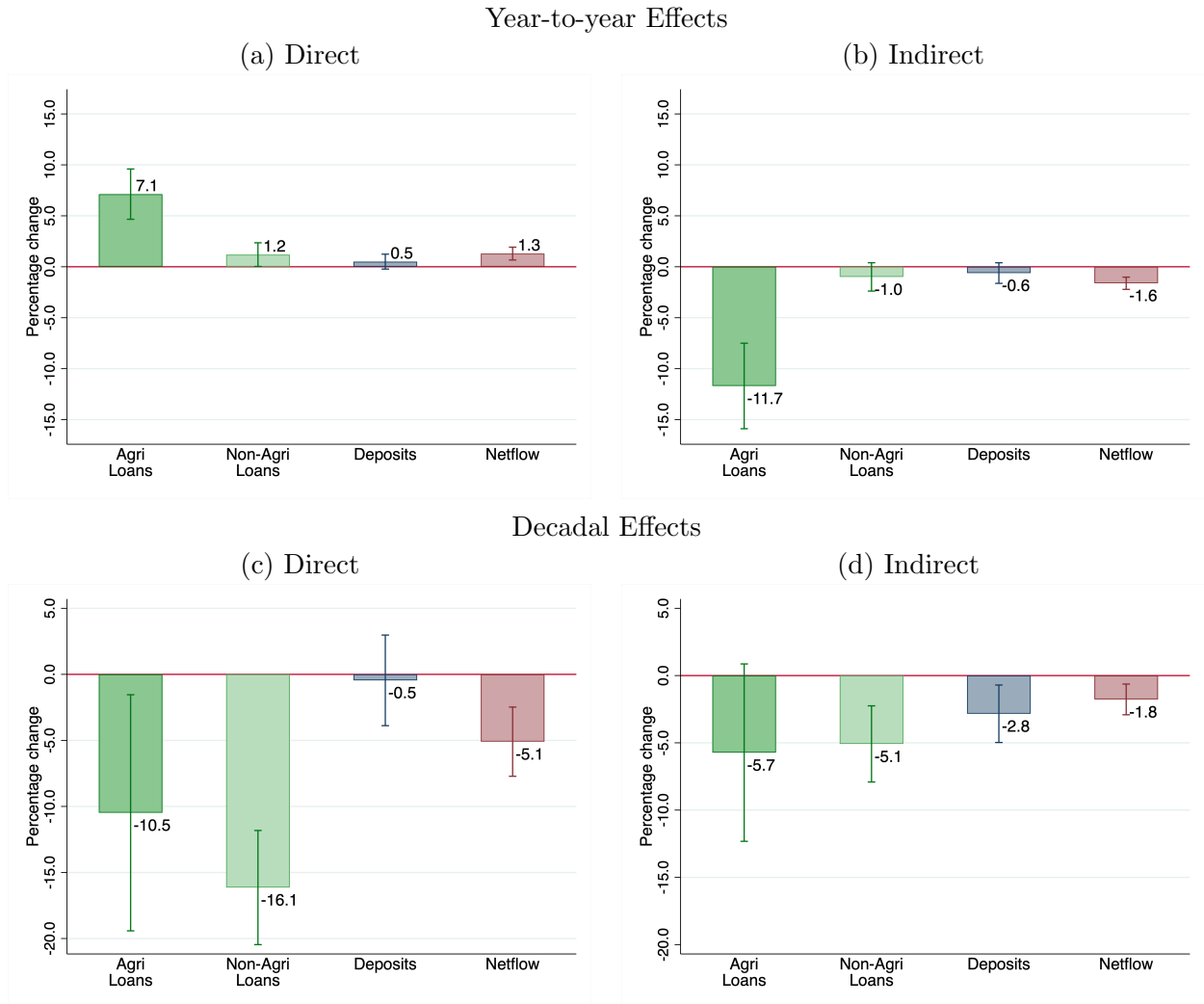
Notes: The figure shows the distribution of *Dryness* ($\text{SPEI} \times -1$) across Brazilian municipalities by decade. The black line in both graphs represents the 50th percentile of the distribution, while the red line in both graphs represents the 90th percentile of the distribution. Quantifications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

FIGURE V: EFFECTS OF EXCESS DRYNESS ON VALUE OF PRODUCTION IN AGRICULTURE BY DECILE OF DRYNESS



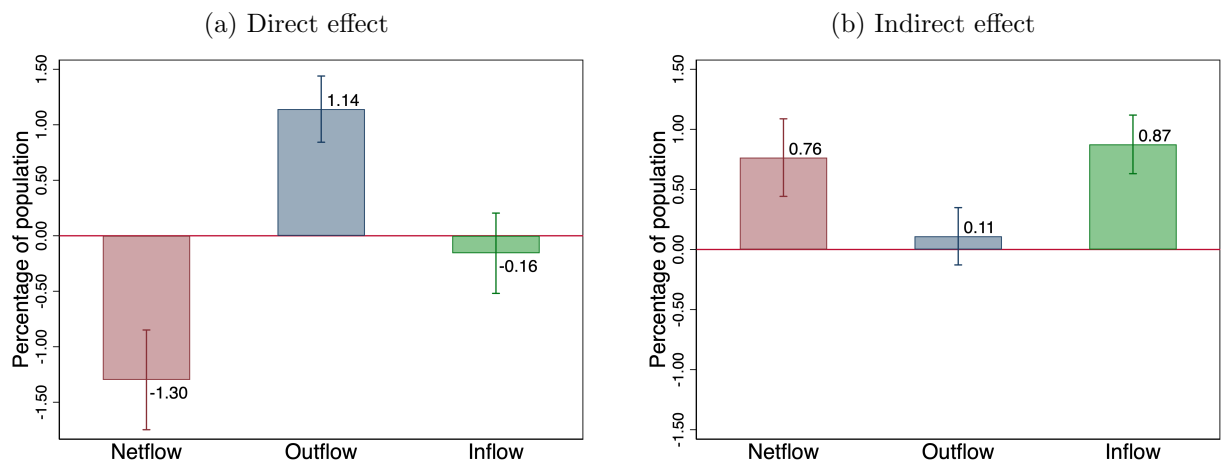
Notes: The figure shows the estimated coefficients on dummies capturing deciles of the excess dryness index in a panel regression at municipality-year level for the period 2000 to 2010 where the outcome variable is the log value of agricultural production for the top 10 crops in Brazil as recorded in the PAM survey. Deciles of *Dryness* go from the wettest to the driest. Estimated effects are relative to the 5th 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 VI: EFFECTS OF EXCESS DRYNESS ON LOANS, DEPOSITS AND CAPITAL FLOWS: YEARLY VS DECADAL EFFECTS



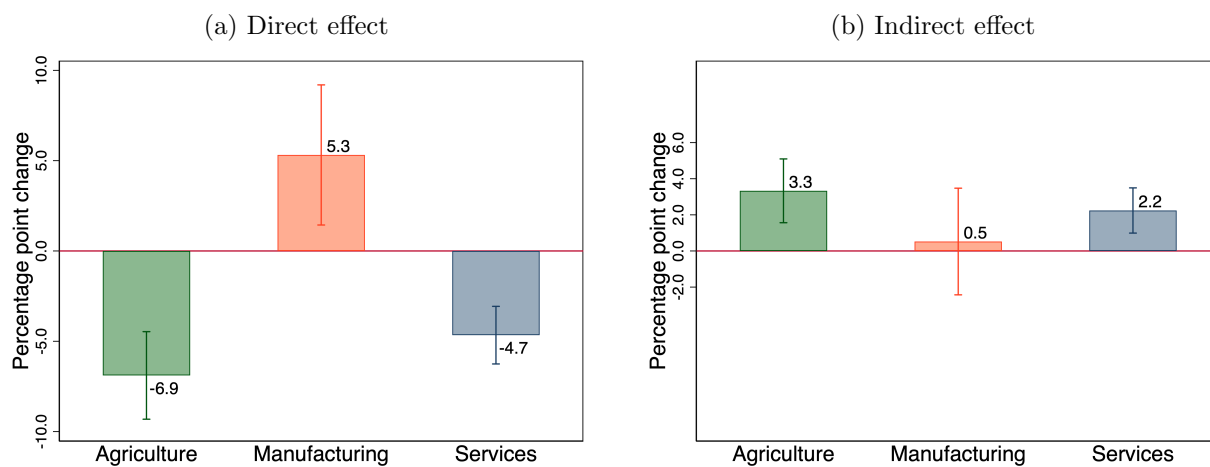
Notes: The figure reports the estimated effects (in percentage points) on capital outcomes for a municipality going from the 50th to the 90th percentile in the direct and indirect (exposure via banks) measures of excess dryness. Panels (a) and (b) report the results for the year-to-year effect of dryness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

FIGURE VII: EFFECTS OF EXCESS DRYNESS ON MIGRATION FLOWS



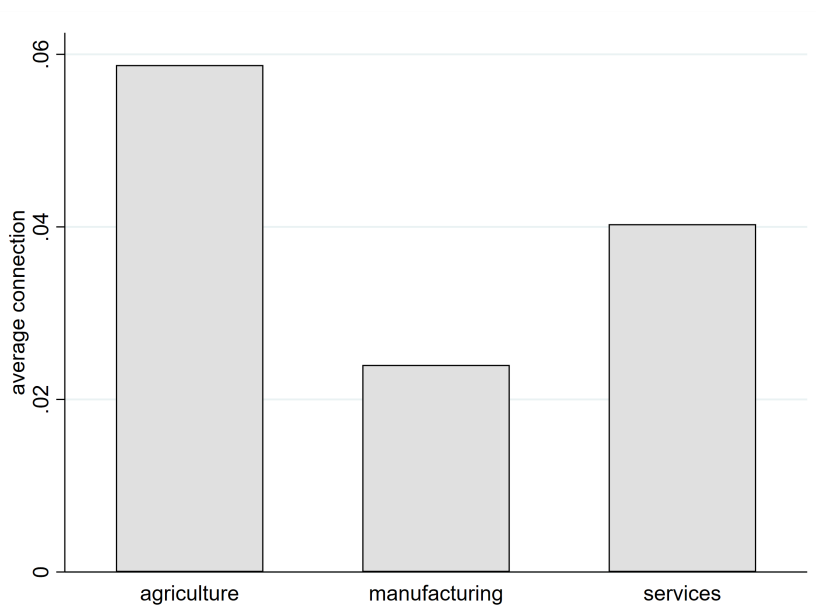
Notes: The figure reports the estimated effects (in percentage points) on the net-, in- and out-migration rate between 2005 and 2010 for a municipality going from the 50th to the 90th percentile in the direct and indirect (exposure via migrant network) measures of excess dryness. Controls include macro-region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

FIGURE VIII: EFFECTS OF EXCESS DRYNESS ON EMPLOYMENT BY SECTOR



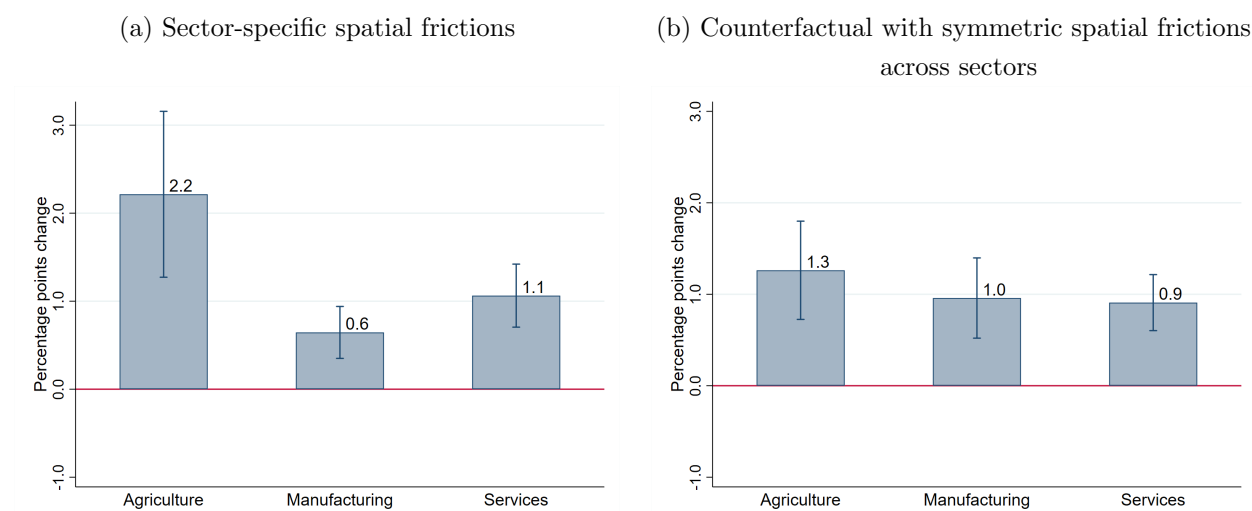
Notes: The figure reports the estimated effects on the log employment in each sector between 2000 and 2010 for a municipality going from the 50th to the 90th percentile in the direct and indirect (exposure via migrant network) measures of excess dryness. Controls include macro-region fixed effects, the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

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 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 X: FIRM EXPOSURE AND EMPLOYMENT GROWTH



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	$\hat{A} < 0$	$L_a \downarrow$	$K_a \downarrow$	$L_m \uparrow$	$K_m \uparrow$	$L_s \downarrow$	$K_s \downarrow$
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 mobile 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: BALANCE TEST

Panel A: Number of reported droughts					
	1(# Droughts =0)	1(# Droughts > 0)	Difference		t-stat
share of rural population	0.387	0.536	0.148	***	7.50
log income per capita	4.719	4.309	-0.410	***	3.88
alphabetization rate	0.768	0.661	-0.107	***	3.13
soy soil suitability	0.271	0.334	0.064	***	2.86
maize soil suitability	0.859	1.132	0.272	***	4.31
Amazon deforestation	0.012	0.002	-0.010	*	1.77
N observations	2,224	2,030			
Panel B: Dryness index					
	1(Dryness \leq median)	1(Dryness > median)	Difference		t-stat
share of rural population	0.440	0.477	0.037		1.47
log income per capita	4.570	4.478	-0.092		0.93
alphabetization rate	0.734	0.700	-0.035		1.24
soy soil suitability	0.285	0.317	0.031		1.33
maize soil suitability	0.951	1.028	0.078		1.05
Amazon deforestation	0.009	0.005	-0.004		0.90
N observations	2,127	2,127			

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

TABLE III: THE EFFECT OF EXCESS DRYNESS ON AGRICULTURAL OUTCOMES

Panel A: Year-to-year regressions 2000-2018				
Outcomes:	log area		log revenues	
	(1)	(2)	(3)	(4)
Δ Dryness	-0.0825*** (0.0127)	-0.0820*** (0.0126)	-0.0821*** (0.0140)	-0.0808*** (0.0141)
Observations	79,160	79,160	79,160	79,160
R-squared	0.905	0.906	0.904	0.905
Year and AMC FE	y	y	y	y
Region x year FE	y	y	y	y
Controls x year FE	n	y	n	y

Panel B: Long-run regressions 2001-2018				
Outcomes:	log area		log revenues	
	(1)	(2)	(3)	(4)
Δ Dryness ₂₀₀₁₋₂₀₁₀	-0.0950* (0.0516)	-0.152*** (0.0527)	-0.176*** (0.0579)	-0.237*** (0.0618)
Observations	4,155	4,155	4,155	4,155
R-squared	0.229	0.267	0.269	0.290
Macro Region FE	y	y	y	y
Controls	n	y	n	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 IV: YEAR-TO-YEAR EFFECTS OF EXCESS DRYNESS ON CAPITAL OUTCOMES
2000-2018

Outcomes:	log loans					log deposits	net flows
	all (1)	all (2)	all (3)	agri (4)	non-agri (5)	(6)	(7)
Δ Dryness	0.0382*** (0.00705)	0.0450*** (0.00749)	0.0341*** (0.00714)	0.0714*** (0.0149)	0.0131* (0.00700)	0.00593 (0.00440)	0.0135*** (0.00381)
Exposure to Dryness via banks		-0.0299*** (0.0105)	-0.0337*** (0.0100)	-0.117*** (0.0255)	-0.0102 (0.00844)	-0.00620 (0.00615)	-0.0164*** (0.00364)
Observations	58,177	58,177	58,124	50,606	58,124	58,124	58,124
R-squared	0.958	0.958	0.960	0.878	0.966	0.979	0.795
Year and AMC FE	y	y	y	y	y	y	y
Regions x year FE	y	y	y	y	y	y	y
Controls x year FE	n	n	y	y	y	y	y

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

TABLE V: DECADAL EFFECT OF DRYNESS ON CAPITAL OUTCOMES
2000-2010

Outcomes:	$\Delta \log$ loans					$\Delta \log$ deposits	Δ net flows
	all (1)	all (2)	all (3)	agri (4)	non-agri (5)	(6)	(7)
$\Delta \text{Dryness}_{2001-2010}$	-0.151*** (0.0233)	-0.150*** (0.0238)	-0.159*** (0.0280)	-0.105* (0.0542)	-0.161*** (0.0262)	-0.00455 (0.0208)	-0.0510*** (0.0159)
Exposure to Dryness via banks		-0.0475** (0.0186)	-0.0729*** (0.0170)	-0.0573 (0.0400)	-0.0508*** (0.0172)	-0.0284** (0.0130)	-0.0177** (0.00693)
Exposure to Dryness via migrants			0.102*** (0.0260)	0.0723 (0.0535)	0.142*** (0.0224)	0.0213 (0.0175)	0.0294** (0.0145)
Observations	2,797	2,797	2,795	2,334	2,795	2,795	2,795
R-squared	0.134	0.141	0.190	0.167	0.227	0.194	0.070
Macro FE	y	y	y	y	y	y	y
Controls	n	n	y	y	y	y	y

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

TABLE VI: DECADAL EFFECT OF DRYNESS ON EMPLOYMENT
2000-2010

Outcomes:	$\Delta \log$ Employment			
	(1)	(2)	(3)	(4)
$\Delta \text{Dryness}_{2001-2010}$	-0.0124** (0.00590)	-0.0250*** (0.00664)	-0.0246*** (0.00703)	-0.0255*** (0.00779)
Exposure to Dryness via migrants		0.0219*** (0.00578)	0.0218*** (0.00588)	0.0217*** (0.00588)
Exposure to Dryness via banks			-0.0120*** (0.00424)	-0.0119*** (0.00424)
Exposure to Dryness via market access				0.00440 (0.0158)
Observations	4,251	4,251	4,247	4,247
R-squared	0.112	0.118	0.134	0.134
Macro-region FE	y	y	y	y
Controls	n	n	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.

TABLE VII: MIGRATION FLOWS
2005-2010

Outcomes:	net migration flows			outflows	inflows
	(1)	(2)	(3)	(4)	(5)
$\Delta\text{Dryness}_{2001-2010}$	-0.00835*** (0.00235)	-0.0129*** (0.00275)	-0.0130*** (0.00273)	0.0114*** (0.00181)	-0.00157 (0.00220)
Exposure to Dryness via migrants		0.00746*** (0.00197)	0.00765*** (0.00196)	0.00110 (0.00145)	0.00875*** (0.00148)
Exposure to Dryness via banks			-0.00130 (0.00150)	-0.00297*** (0.00100)	-0.00428*** (0.00130)
Observations	4,247	4,247	4,247	4,247	4,247
R-squared	0.224	0.229	0.229	0.211	0.298
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 VIII: DECADAL EFFECT OF DRYNESS ON EMPLOYMENT BY SECTOR
2000-2010

Outcomes:	$\Delta \log$ Employment		
	agri (1)	manuf (2)	serv (3)
$\Delta \text{Dryness}_{2001-2010}$	-0.0689*** (0.0147)	0.0532** (0.0235)	-0.0466*** (0.00968)
Exposure to Dryness via migrants	0.0333*** (0.0107)	0.00524 (0.0179)	0.0224*** (0.00759)
Exposure to Dryness via banks	0.0152* (0.00834)	-0.0916*** (0.0160)	-0.00314 (0.00563)
Observations	4,247	4,240	4,247
R-squared	0.072	0.100	0.095
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.

TABLE IX: WORKERS' FLOWS TO FIRMS EXPOSED TO DRYNESS

Outcomes:	$\frac{L_{oi(d)2006-2010}}{Lavg_i}$								
	All firms			by Sector			by Size		
	(1)	(2)	(3)	agri (4)	manuf (5)	services (6)	small (7)	medium (8)	large (9)
firm connection to origin $\times 1(\text{SPEI-12} < \text{p25})$		0.209*** (0.0375)	0.322*** (0.0480)	0.486*** (0.0798)	0.369*** (0.0738)	0.350*** (0.0484)	0.657*** (0.0494)	0.444*** (0.0351)	0.255*** (0.0545)
firm connection to origin	0.621*** (0.0132)	0.424*** (0.0156)	0.506*** (0.0198)	0.561*** (0.0470)	0.436*** (0.0213)	0.502*** (0.0285)	0.388*** (0.0174)	0.479*** (0.0167)	0.529*** (0.0224)
$1(\text{SPEI-12} < \text{p25})$		-0.139*** (0.0164)	-0.132*** (0.0153)	-0.112*** (0.0160)	-0.135*** (0.0142)	-0.179*** (0.0203)	-0.193*** (0.0178)	-0.145*** (0.0145)	-0.122*** (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 : $\frac{L_{i(m),t^*,o \rightarrow d}}{L_{i(m),t^*}}$.

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

$$Y_a = A_a T^\beta (K_a^\gamma L_a^{1-\gamma})^{1-\beta} \quad (\text{A1})$$

$$Y_m = A_m K_m^\gamma L_m^{1-\gamma} \quad (\text{A2})$$

$$Y_s = A_s K_s^\gamma L_s^{1-\gamma} \quad (\text{A3})$$

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

$$\frac{K_i}{L_i} = \frac{K}{L} = \frac{\gamma}{1-\gamma} \frac{w}{r_k} \quad (\text{A4})$$

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

$$\frac{X_i}{X} = \frac{K_i}{K} = \frac{L_i}{L} \quad (\text{A5})$$

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

Agriculture Profit maximization in agriculture implies

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

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

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

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

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

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

Services Aggregate demand for services is

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

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

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

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

Manufacturing Labor and capital factor market clearing imply:

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

which together with (A5) yields:

$$\frac{X_m}{X} = 1 - \frac{X_a}{X} - \frac{X_s}{X} \quad (\text{A11})$$

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:

$$\begin{aligned}\hat{w} &= \gamma (\hat{K} - \hat{L}) \\ \hat{r}_k &= -(1 - \gamma) (\hat{K} - \hat{L})\end{aligned}$$

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 $\hat{K}_a - \hat{K} = \hat{K}_a - \hat{K}$ from differentiating (A4), we obtain

$$\begin{aligned}\hat{L}_a &= \gamma (\hat{L} - \hat{K}) \\ \hat{K}_a &= (1 - \gamma) (\hat{K} - \hat{L}) \\ (\hat{L}_a/L) &= (\gamma - 1) \hat{L} - \gamma \hat{K} \\ (\hat{K}_a/K) &= (\gamma - 1) (\hat{L}) - \gamma \hat{K}\end{aligned}$$

- 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 EXCESS DRYNESS AND REPORTED DROUGHTS

Although reported droughts cannot be used for identification because of endogeneity concerns (Panel A of Table II and discussion in section III.A), drought reports are a useful benchmark to evaluate if SPEI indeed captures dryness conditions considered so extreme by local authorities to require federal assistance. To investigate if reported droughts coincide in terms of timing with dryness measured by SPEI, we perform an event-study analysis by regressing *Dryness* on twelve leads and twelve lags of reported droughts using a monthly panel at the municipality level. More specifically, we estimate the following equation:

$$Dryness_{mt} = \alpha + \sum_{k=-12}^{12} \beta_k drought_{mt}^k + \varepsilon_{mt}, \quad (B1)$$

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

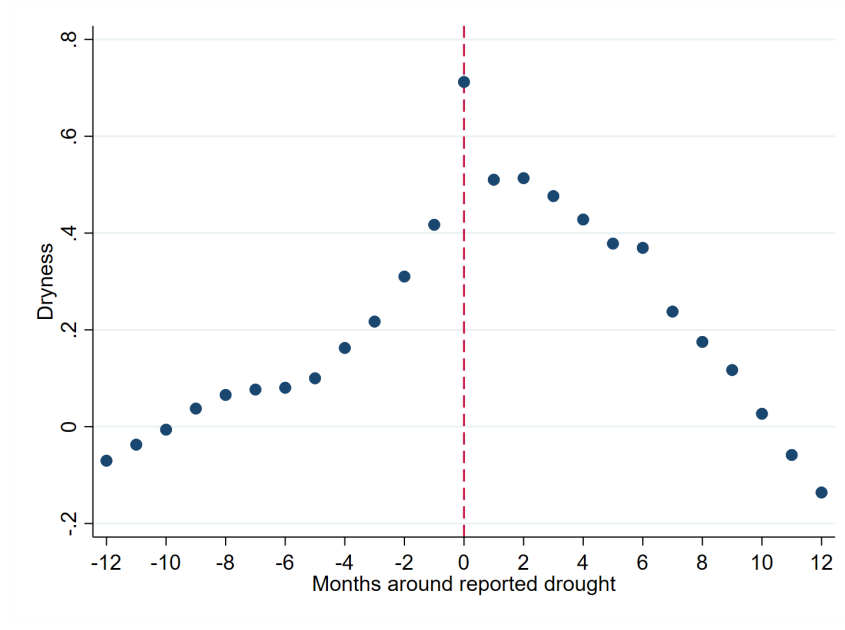
Figure B1 plots the coefficients β_k . As shown, the deviation of *Dryness* from its mean is the highest in the month a drought is reported, around 0.7 standard deviations above the long run average dryness of that location. The figure also shows that dry weather is registered well ahead of the month a drought is reported, starting to be significantly above the long-run average around four months earlier. This suggests that the incidence of dry weather over several months is what usually triggers a report. Furthermore, the *Dryness* continues to be high during several months after the report, still being around 0.4 above the long-run average six months after a drought event is reported.

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

$$drought_{mt} = \alpha_m + \alpha_t + \alpha_{rt} + \beta Dryness_{mt} + \Lambda X_m \times d_t + \varepsilon_{mt}, \quad (B2)$$

where the outcome variable is the number of reported droughts in the SINPDEC data in a given municipality and year and the main explanatory variable is excess *Dryness*. All specifications include macro-region (r) fixed effects interacted with year fixed effects, as well as the initial municipality controls used in Table II (X_m) interacted with year fixed effects (d_t). We report coefficient estimates for this specification separately for the first and second decade of the 2000s in columns (1) and (2) of Table B1. Next, we report pooled estimates for the 2000-2018 period for which we observe both droughts and *Dryness* in column (3). As shown, higher dryness relative to historical averages strongly predicts a higher probability that a municipality reports more droughts to the federal government. The magnitude of the estimated coefficient in column (3) indicates that a municipality moving from the median to the 90th percentile of *Dryness* experienced 8 percent more droughts per year in the 2000 to 2018 period.

FIGURE B1: AVERAGE EXCESS DRYNESS INDEX AROUND DROUGHT EVENTS



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

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

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

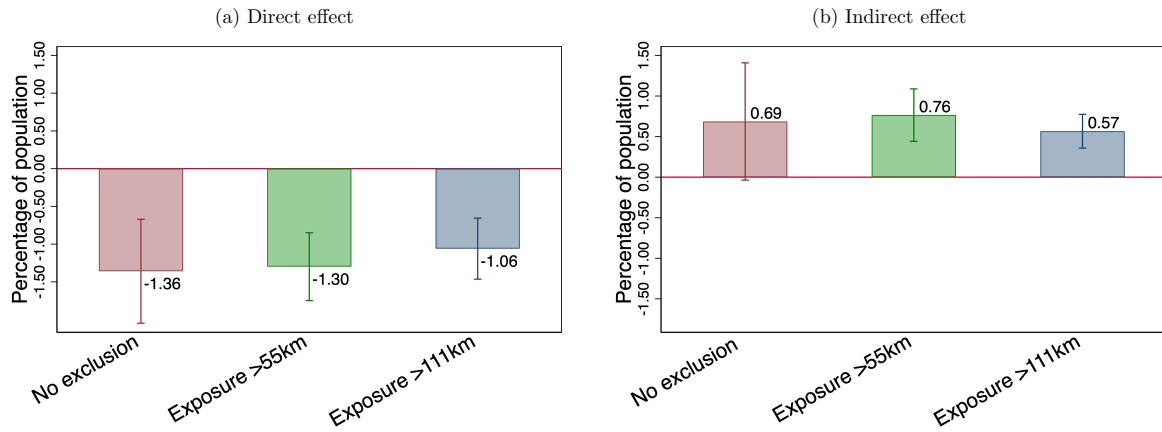
TABLE B1: REPORTED DROUGHTS AND EXCESS DRYNESS

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

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

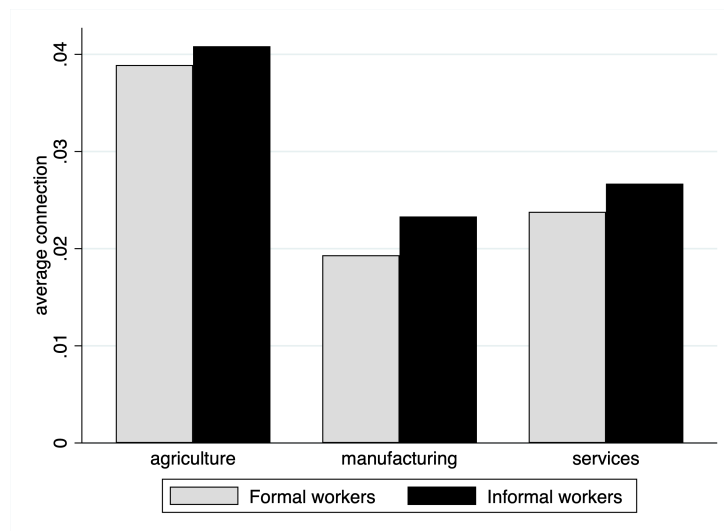
C ADDITIONAL FIGURES AND TABLES

FIGURE C1: EFFECTS OF EXCESS DRYNESS ON THE NET MIGRATION RATE
DIAGNOSTICS ON SPATIAL CORRELATION



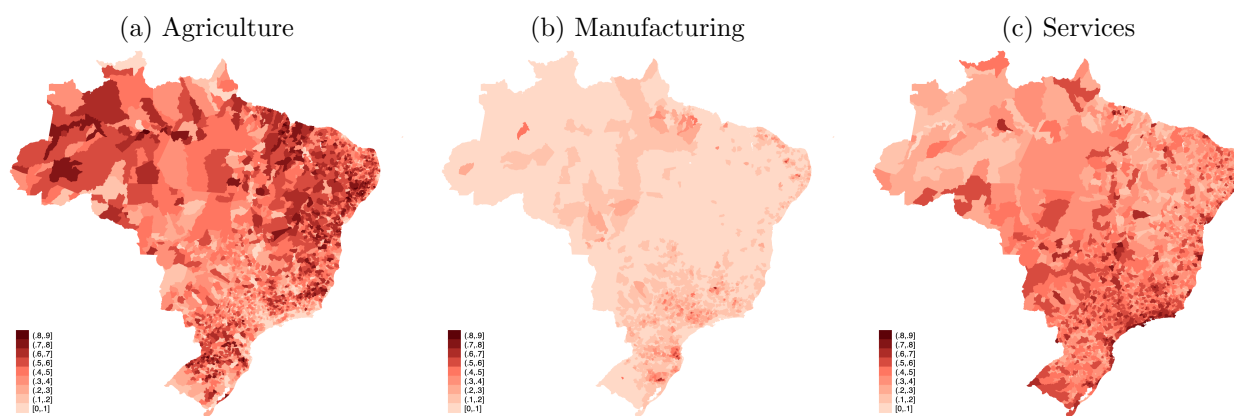
Notes: The figure reports the estimated effects on the net migration flow relative to population during the 2005 to 2010 period for a municipality going from the 50th to the 90th percentile in the direct and indirect (exposure via migrant network) measures of excess dryness. We report the estimated coefficients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

FIGURE C2: MUNICIPALITY INITIAL CONNECTIONS TO HIGH EXCESS DRYNESS AREAS



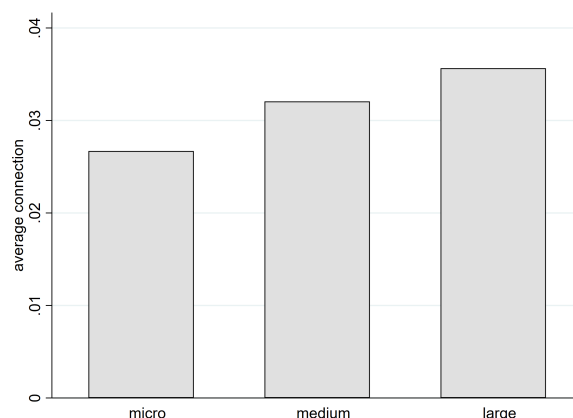
Notes: The figure shows the average connection α_{om} of municipalities m to origins o that are in the top quartile of dryness by sector. The connection is calculated as the share of workers employed in the baseline year 2000 who moved from origin municipality o to the destination municipality m during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

FIGURE C3: GEOGRAPHICAL DISTRIBUTION OF SECTORAL EMPLOYMENT SHARES



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

FIGURE C4: 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.

TABLE C1: CORRELATION BETWEEN MEASURES OF EXPOSURE

	Δ Dryness	Exposure via banks	Exposure via migrants
Δ Dryness	1.000		
Exposure via banks	0.110 0.000	1.000	
Exposure via migrants	0.643 0.000	0.157 0.000	1.000

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

TABLE C2: DECADAL EFFECT OF DRYNESS ON POPULATION AND WAGES
2000-2010

Outcomes:	$\Delta \log \text{Pop}$		$\Delta \log \text{wage}$	
	(1)	(2)	(3)	(4)
$\Delta \text{Dryness}_{2001-2010}$	-0.0484*** (0.00654)	-0.0490*** (0.00648)	0.0115 (0.00775)	0.0120 (0.00787)
Exposure to Dryness via migrants	0.0229*** (0.00442)	0.0242*** (0.00442)	0.0118* (0.00657)	0.0106 (0.00673)
Exposure to Dryness via banks		-0.00928*** (0.00335)		0.00678 (0.00488)
Observations	4,247	4,247	4,247	4,247
R-squared	0.208	0.211	0.166	0.167
Macro-region FE	y	y	y	y
Controls	y	y	y	y

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

TABLE C3: ROBUSTNESS OF CAPITAL EFFECTS TO CLUSTERING AT MESOREGION LEVEL

Panel A: Yearly Effects

Outcomes:	log loans					log deposits	net flows
	all (1)	all (2)	all (3)	agri (4)	non-agri (5)	(6)	(7)
Δ Dryness	0.0382*** (0.0102)	0.0450*** (0.0114)	0.0341*** (0.00795)	0.0714*** (0.0190)	0.0131 (0.00897)	0.00593 (0.00746)	0.0135*** (0.00423)
Exposure to Dryness via banks		-0.0299* (0.0168)	-0.0337** (0.0159)	-0.117*** (0.0391)	-0.0102 (0.0129)	-0.00620 (0.00955)	-0.0164*** (0.00538)
Observations	58,177	58,177	58,124	50,606	58,124	58,124	58,124
R-squared	0.958	0.958	0.960	0.878	0.966	0.979	0.795
Year and AMC FE	y	y	y	y	y	y	y
Regions x year FE	y	y	y	y	y	y	y
Controls x year FE	n	n	y	y	y	y	y

Panel B: Decadal Effects

Outcomes:	Δ log loans					Δ log deposits	Δ net flows
	all (1)	all (2)	all (3)	agri (4)	non-agri (5)	(6)	(7)
Δ Dryness _{2001–2010}	-0.151*** (0.0322)	-0.150*** (0.0345)	-0.159*** (0.0361)	-0.105 (0.0708)	-0.161*** (0.0313)	-0.00455 (0.0266)	-0.0510** (0.0208)
Exposure to Dryness via banks		-0.0475 (0.0298)	-0.0729*** (0.0244)	-0.0573 (0.0663)	-0.0508* (0.0279)	-0.0284 (0.0242)	-0.0177 (0.0112)
Exposure to Dryness via migrants			0.102*** (0.0296)	0.0723 (0.0620)	0.142*** (0.0271)	0.0213 (0.0231)	0.0294* (0.0161)
Observations	2,797	2,797	2,795	2,334	2,795	2,795	2,795
R-squared	0.134	0.141	0.190	0.167	0.227	0.194	0.070
Macro FE	y	y	y	y	y	y	y
Controls	n	n	y	y	y	y	y

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

TABLE C4: ROBUSTNESS OF EMPLOYMENT AND MIGRATION EFFECTS TO CLUSTERING AT MESOREGION LEVEL

Outcomes:	$\Delta \log$ Employment				netflows (5)	outflows (6)	inflows (7)
	all (1)	agri (2)	manuf (3)	serv (4)			
$\Delta \text{Dryness}_{2001-2010}$	-0.0255*** (0.00862)	-0.0689*** (0.0195)	0.0532* (0.0310)	-0.0466*** (0.0135)	-0.0130*** (0.00345)	0.0114*** (0.00258)	-0.00157 (0.00313)
Exposure to Dryness via migrants	0.0217*** (0.00593)	0.0333** (0.0143)	0.00524 (0.0188)	0.0224*** (0.00769)	0.00765*** (0.00226)	0.00110 (0.00191)	0.00875*** (0.00158)
Exposure to Dryness via banks	-0.0119** (0.00548)	0.0152 (0.0104)	-0.0916*** (0.0218)	-0.00314 (0.00769)	-0.00130 (0.00183)	-0.00297** (0.00115)	-0.00428** (0.00198)
Observations	4,247	4,247	4,240	4,247	4,247	4,247	4,247
R-squared	0.134	0.072	0.100	0.095	0.229	0.211	0.298
Macro-region FE	y	y	y	y	y	y	y
Controls	y	y	y	y	y	y	y

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

TABLE C5: ROBUSTNESS OF POPULATION AND WAGE EFFECTS TO CLUSTERING AT MESOREGION LEVEL

Outcomes:	$\Delta \log \text{Pop}$		$\Delta \log \text{wage}$	
	(1)	(2)	(3)	(4)
$\Delta \text{Dryness}_{2001-2010}$	-0.0484*** (0.00980)	-0.0490*** (0.00941)	0.0115 (0.0115)	0.0120 (0.0119)
Exposure to Dryness via migrants	0.0229*** (0.00487)	0.0242*** (0.00479)	0.0118 (0.00842)	0.0106 (0.00869)
Exposure to Dryness via banks		-0.00928* (0.00487)		0.00678 (0.00728)
Observations	4,247	4,247	4,247	4,247
R-squared	0.208	0.211	0.166	0.167
Macro-region FE	y	y	y	y
Controls	y	y	y	y

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