THE EFFECTS OF CLIMATE CHANGE ON LABOR AND CAPITAL REALLOCATION

CHRISTOPH ALBERT
Collegio Carlo Alberto

PAULA BUSTOS
ICREA, UPF, BSE and CEPR

JACOPO PONTICELLI
Northwestern, NBER and CEPR

Climate change is expected to reduce agricultural productivity in developing countries. Classic trade and geography models predict that the optimal adaptation response is a reallocation of capital and labor from agriculture towards sectors and regions gaining comparative advantage. In this paper, we provide evidence on the effects of recent changes in climate in Brazil to understand to what extent factor market frictions constrain this reallocation process. We document that persistent increases in dryness do not generate capital reallocation but a sharp reduction in credit to all sectors in both drying areas and financially integrated regions. In addition, dryness generates a large reduction in agricultural employment. Workers staying in drying regions reallocate towards manufacturing but climate migrants are allocated to small firms outside of manufacturing in destination regions. The evidence suggests that frictions in the interbank market and spatial labor market frictions constrain the reallocation process from agriculture to manufacturing.

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

Christoph Albert: christoph.albert@carloalberto.org

Paula Bustos: paula.bustos@upf.edu

Jacopo Ponticelli: jacopo.ponticelli@kellogg.northwestern.edu

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1. INTRODUCTION

Global warming is expected to generate a reduction in precipitation in subtropical regions, leading to large agricultural productivity losses (IPCC 2021). Classic international trade and geography models predict that the optimal adaptation response is a reallocation of capital and labor from agriculture towards other sectors or regions gaining comparative advantage.[1] However, developing economies are characterized by labor and capital market frictions which can constrain this structural transformation process.[2] In this paper, we provide direct evidence on the effects of recent changes in climate in Brazil on factor reallocation across sectors and regions and confront it with the predictions of a classic open economy model. We find that local factor reallocation across sectors in response to climate change follows the optimal adjustment path predicted by the model. However, factor reallocation across regions is constrained by spatial capital and labor market frictions.

Brazil is particularly suited for this analysis because its climate already started experiencing the effects of global warming highlighted by climate science. We document a worsening of meteorological drought conditions in the last two decades relative to the past century.[3] These increases in dryness are heterogeneous across Brazilian regions but uncorrelated with their initial level of development. As a result, we can exploit them to estimate the direct effects of climate change on labor and capital allocation across sectors within each region, as well as the indirect effects of climate change in regions that are the destination of factor flows originated by climate shocks.

To interpret our estimates of the direct and indirect effects of changes in dryness on factor reallocation, we extend the classic Ricardo-Viner model (Dixit and Norman 1980). The model describes a small open economy corresponding to the local labor and capital markets in each municipality. In this neoclassical framework, factor allocation across the two tradable sectors – agriculture and manufacturing – depends on comparative advantage,

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

[2] Goldberg and Pavcnik (2007); De Mel et al. (2008); Buera, Kaboski, and Shin (2011); Gollin et al. (2014); McCaig and Pavcnik (2018); Munshi (2020); Porzio et al. (2022); Donovan and Schoellman (2023).

[3] Climate 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). Indeed, we also document an increase in the frequency of droughts reported by municipalities to the federal government using newly digitized administrative data from the National System of Civil Protection in Brazil (SINPDEC).

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

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

The empirical analysis aims at studying both the direct effects of changes in dryness on the local labor and capital markets of affected municipalities, and the indirect effects on municipalities whose factor markets are integrated with areas experiencing changes in dryness. To implement this analysis we use an empirical framework which combines regional climate shocks with measures of market integration across regions. This methodology permits to construct, for each region, a measure of indirect exposure to climate shocks in other regions integrated through labor or capital markets. Extending the empirical analysis to include this indirect exposure measure is important not only to estimate indirect effects but also to obtain unbiased estimates of direct effects whenever shocks are spatially correlated (Donaldson and Hornbeck 2016; Adao, Arkolakis, and Esposito 2019; Borusyak, Dix-Carneiro, and Kovak 2023).

We capture regional dryness shocks driven by climate change through a meteorological measure of drought conditions, the Standardized Precipitation and Evapotranspiration Index, or SPEI (Vicente-Serrano et al. 2010). This index measures standard deviations in drought conditions relative to a 100-year average ("excess dryness"), driven by changes in both temperature and rainfall. We document large variation in this measure across Brazilian municipalities, and show that decadal changes in 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 strategy to identify the local effects of climate change on factor allocation.

In addition to the direct effect of local climate shocks, our empirical specification incorporates the indirect effects of climate shocks in other regions integrated through capital and labor markets. 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 addition, we construct a measure of labor market integration across municipalities using past migrant networks and track contemporaneous migration flows using Population Census data. We address potential concerns regarding separate identification of goods, labor and capital market linkages in two ways. First, we control for a measure of goods market integration using the transport network. Second, we construct a firm-level measure of labor market integration with each potential origin municipality using the employment histories of migrant workers from social security data.

We start our empirical analysis by documenting that, indeed, regions subject to persistent abnormally dry meteorological conditions experience a significant reduction in agricultural production. A municipality moving from the median to the 90th percentile of excess dryness during the last two decades relative to the past century experienced a 10% reduction in the value of agricultural output per decade. Estimated effects are highly non-linear with sharp reductions in output in the top deciles of dryness but no significant effects of excess wetness. This large output reduction suggests a limited scope for adaptation responses within the agricultural sector, like adopting new technologies or changes in crop composition. Existing estimates of expected welfare losses in agricultural markets from climate change are significantly larger in this scenario (Costinot, Donaldson, and Smith 2016).

We continue by studying the direct and indirect effects on capital reallocation of both short-run weather shocks, measured by yearly variation in dryness, and long-run climate change, measured as the difference between dryness in a given decade and the previous century. Our findings indicate that, in the short-run, the financial system favors risk sharing between regions affected by weather shocks and financially connected regions. In particular, we find that regions suffering droughts experience capital inflows and an increase in credit to the agricultural sector while financially connected regions reduce credit and experience capital outflows. This finding suggests that banks smooth temporary income shocks by reallocating capital across regions where they have branches.

However, over the long-run, the evidence is inconsistent with the predictions of classic open economy models. First, with respect to the direct effect, our model predicts that a reduction in agricultural productivity leads to a reallocation of capital towards local manufacturing. Instead, we find that capital reallocates away from both local agriculture and non-agriculture. Specifically, a municipality experiencing an increase in dryness from the median to the 90th percentile experiences a 15 percent decadal decline in lending originated by local branches to all sectors of the economy. Second, with respect to the indirect effect, classic models of capital flows predict that, under financial integration, a negative productivity shock in a region generates a reallocation of capital away from that region into other regions which are financially integrated (Mundell 1957). In contrast, we find negative indirect effects on lending to all sectors in municipalities that are financially integrated with areas experiencing increases in dryness. In addition, we find that this contraction in credit leads to a large reduction in manufacturing employment.

Overall, these results suggest that the financial system is able to smooth the negative effects of short-run weather shocks but that persistent droughts have negative spillovers on non-agricultural sectors both locally and in financially integrated regions, which stands in sharp contrast with our benchmark neoclassical model. In turn, the finding that the contraction in credit in indirectly affected regions leads to a reduction in manufacturing employment is consistent with the hypothesis that manufacturing is more vulnerable to credit frictions due to large fixed costs (Buera, Kaboski, and Shin 2011). Thus, capital market frictions appear to be a key constraint for optimal factor adjustment in response to climate change.

Turning to the direct effects of dryness on labor reallocation, we find that municipalities experiencing an increase in dryness from the median to the 90th percentile over the 2001-2010 period suffer a sharp reduction in employment in both agriculture (-6.9%) and services (-4.7%), and 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 services. Yet, 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. As a result, a municipality moving from the median to the 90th percentile of decadal increases in dryness experiences a 4.9 percent reduction in population.

Next, we follow climate migrants to study the indirect effects on their destination municipalities. We confirm that municipalities integrated through past migrant networks with areas suffering droughts experience a large increase in migration inflows, as in Munshi (2003). However, these regions only expand employment in agriculture and services, not in manufacturing. This is not consistent with our neoclassical model, which predicts that an inflow of labor reinforces the comparative advantage of manufacturing with respect to agriculture, which is intensive in the fixed factor (land). As a result, in the model, immigrants are allocated to manufacturing because allocating them into agriculture would generate decreasing returns.

In sum, the model predicts that displaced agricultural workers should reallocate towards manufacturing both locally and in their destination after migration. However, we only find local reallocation towards manufacturing in regions directly hit by excess dryness. This suggests that local labor reallocation across sectors is relatively unconstrained while spatial reallocation from agriculture to manufacturing is subject to labor market frictions. In the last part of the paper, we investigate this potential source of frictions using social security data (Annual Social Information System, RAIS).

We infer labor market frictions across sectors and regions using past labor flows. This interpretation is based on the predictions of economic geography models where bilateral migration flows are a function of bilateral migration costs (Berkes, Gaetani, and Mestieri 2022; Borusyak et al. 2023). These costs could reflect transportation or other labor market frictions such as search and matching costs. We use the social security data to construct 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. If spatial 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 each potential origin. However, we find that in the baseline period only 2 percent of workers employed by the average manufacturing firm came from areas which would be subject to droughts in the following decade, compared to 4 percent in services and 6 percent in agriculture. This implies that climate migrants face larger frictions to match with manufacturing firms in the average destination. We show that this is because manufacturing is concentrated in space and thus tends to source labor from local labor markets that are distant from the average rural area, as in Krugman (1991).

The asymmetry in spatial labor market frictions across sectors documented above can potentially explain the mismatch between our findings and the predictions of our model. To quantify the importance of this explanation, we provide micro-estimates of the indirect effects of excess dryness via migrant networks using employer-employee data. We document that firms in the manufacturing sector display a lower elasticity of employment to labor supply shocks driven by climate migrants from origins connected through past migrant networks. Next, we show that this gap in labor demand elasticity across sectors is fully accounted for by differences in spatial labor market frictions across sectors.[4]

Our findings imply that spatial capital and labor market frictions are a major constraint to factor reallocation in response to climate change. The optimal response to lower agricultural productivity would be a reallocation of both factors towards the other traded sector, manufacturing, which is concentrated in space. As a result, a large part of this reallocation process needs to take place across regions. However, we find that spatial capital and labor market frictions constrain spatial factor reallocation towards manufacturing.

Related Literature

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

[4]An alternative explanation for this lack of spatial labor reallocation into manufacturing is that workers displaced by drier climatic conditions – especially former agricultural workers – might not have the skills required for manufacturing in destination regions. In this case, the absence of reallocation into manufacturing would not reflect spatial frictions but an optimal allocation of labor. We show that neither low-skill nor high-skill workers relocate into manufacturing, which suggests that labor market frictions play a role.

With respect to capital reallocation, there is a rich literature on risk-sharing mechanisms in rural communities exposed to weather shocks (Townsend 1994, Udry 1994, 1995, Fafchamps et al. 1998, Casaburi and Willis 2018). However, there is limited work on risk-sharing through capital market integration across regions.[5] More importantly, to the best of our knowledge, there is no evidence on the effects of long-run climate changes on capital allocation across regions. We contribute to this literature by documenting the direction and magnitude of capital flows across small geographical units within a developing country in response to both short-run weather shocks and long-run changes in climate. In particular, our finding that persistent droughts in rural areas can have negative effects on credit and manufacturing employment in distant regions through financial linkages is novel.

With respect to labor reallocation, a few recent empirical studies focus on the effects of climate change on urbanization and structural transformation. Henderson et al. (2017) show that long-term increases in dryness in sub-saharan Africa only had positive effects on urbanization in regions where cities are likely to be manufacturing centers. They interpret their findings in light of a small open economy model where agricultural labor can only reallocate towards traded manufacturing given the reduction in demand for services. Our findings for the local effects of droughts in Brazil are in line with their interpretation while our findings for the indirect effects point in a different direction. We do find that a third of workers displaced by droughts reallocate away from both agriculture and services into local manufacturing. However, most of the adjustment takes place through out-migration flows and migrants do not find jobs in manufacturing in destination regions. This is because, even in the presence of manufacturing firms at destination, asymmetric spatial labor market frictions direct migrants towards jobs in agriculture or services.

Recent empirical studies in India by Emerick (2018), Santangelo (2019) and Colmer (2021) show that short-run weather shocks induce local labor reallocation across sectors but do not induce migration. In turn, contemporaneous work by Liu et al. (2023) shows that long-term increases in temperature in India generate an increase in the local agricultural employment share and no out-migration. Our findings for the local effects of persistent droughts in Brazil have the opposite sign: a reduction in the local agricultural employment

[5] Yang (2008) documents that international financial flows – in particular foreign aid and remittances – help developing countries absorb the economic impact of natural disasters, and Asdrubali et al. (1996) provides evidence consistent with US states smoothing income shocks via borrowing and lending on national credit markets.

share and large out-migration flows. This difference in findings for India and Brazil is informative about the relevant margins of adjustment to climate change for countries with different levels of internal market integration. The findings for India can be rationalized by a model with large spatial frictions in both goods and labor markets.[6] In this case, Nath (2022) shows that if agriculture is a subsistence good, then the reduction in local agricultural income can increase employment in local agriculture. In contrast, in Brazil, agricultural and manufacturing goods are traded, with limited subsistence agricultural activities. Thus, a reduction in local agricultural productivity leads to labor reallocation towards local manufacturing. Similarly, regional labor markets are more integrated than in India so that large part of the adjustment takes place through out-migration.[7]

Our empirical methodology builds on the literature studying the effects of regional weather and climate shocks on local economic outcomes (Paxson 1992; Jayachandran 2006; Burgess and Donaldson 2010; Dell et al. 2012; Burke and Emerick 2016; Kaur 2019). We contribute to this literature by using an empirical framework which takes into account not only local changes in climate but also shocks to other regions integrated through labor and capital markets. We combine this framework with detailed data on capital and labor flows, which permits to directly observe factor reallocation across sectors and regions. We document strong migration and capital outflow responses to persistent increases in dryness. This finding underlines the importance of studying how climate-related shocks propagate across space via existing labor market and financial networks. In this respect, our paper is related to the literature on the spillover effects of regional trade and technology shocks (Redding and Venables 2004; Donaldson and Hornbeck 2016; Bustos et al. 2020; Fajgelbaum et al. 2021; Imbert et al. 2022). In particular, Allen and Atkin (2022) study how weather shocks propagate across regions through agricultural goods markets in India. We contribute to this literature by studying how climate shocks propagate across space through capital and labor flows.

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

[7]Consistent recent evidence by Peri and Sasahara (2019) documents that higher temperatures trigger internal migration in middle- but not in low-income countries. In the context of Brazil, Brunel and Liu (2020) estimate that higher temperatures increase inter-state migration flows.

Finally, our paper is related to the recent literature developing quantitative trade and spatial models to estimate the effects of future changes in climate on the spatial allocation of population and economic activity (Desmet and Rossi-Hansberg 2015; Balboni 2019; Conte et al. 2021; Nath 2022). The quantitative predictions of these models largely depend on the extent to which factor market frictions constrain the optimal adjustment to climate change. We thus think that our finding that spatial capital market frictions constrain adaptation to climate change highlights the relevance of incorporating capital flows across regions in quantitative spatial models, as in recent work by Kleinman et al. (2023). In addition, our finding that asymmetric spatial labor market frictions constrain the factor reallocation process from the agricultural sector in directly affected regions to manufacturing in other regions can be used to inform the values of spatial labor market frictions in counterfactual analysis.

2. 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.[8] Then, we use the model

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

to predict the effects of local agricultural productivity decline on local factor markets. We call these the direct effects of climate change.

In the empirical analysis, we study the spillover effects of climate change through factor flows which are exogenous from the point of view of the destination municipality. We do a parallel comparative statics exercise in the model: we 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. Note that, as a result, we do not model factor flows across regions explicitly.[9]

2.1. *Model Setup*

We present a classic small open economy model where goods and factor markets are perfectly competitive. There are two traded sectors, agriculture (a) and manufacturing (m) and one non-traded sector, services (s). Trade costs are assumed to be zero so that prices for agricultural and manufacturing goods are determined in international markets. Preferences over consumption of the three goods are Cobb-Douglas with expenditure shares α_i for each good $i = a, m, s$. There are three production factors in fixed supply within each region: land (T), capital (K) and labor (L). We assume that agricultural production uses the three factors, under constant returns to scale: $Q_a = A_a T_a^{\beta}(K_a^{\gamma} L_a^{1-\gamma})^{1-\beta}$. In turn, manufacturing and services only use capital and labor: $Q_m = A_m K_m^{\gamma} L_m^{1-\gamma}$; $Q_s = A_s K_s^{\gamma} L_s^{1-\gamma}$, where $0 < \beta < 1$, $0 < \gamma < 1$, and A_i are productivity parameters for each sector $i = a, m, s$. Note that because all sectors use capital and labor in the same proportions, we can think of them as a composite mobile factor $X = K^{\gamma} L^{1-\gamma}$. As a result, the model inherits the workings of a textbook Ricardo-Viner model as described by Dixit and Norman (1980).[10]

[9] State of the art quantitative spatial models include labor flows across regions and capital accumulation, but they do not simultaneously display capital flows across regions (Kleinman et al. 2023).

[10] For a 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.

2.2. *Equilibrium*

In this section we describe the main features of equilibrium, which are derived formally in Appendix sections A.1.1 and A.1.2.

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.

Equilibrium factor allocation across sectors. The equilibrium employment share in agriculture is increasing in its comparative advantage with respect to manufacturing, which is determined by the two classic supply-side forces. First, Ricardian comparative advantage, given by relative agricultural productivity (A_a/A_m). Second, Hecksher-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 demand for services is a constant share (α_s) of income $(wL + r_k K + r_T T)$. Thus, in equilibrium the employment share in services is increasing in income per-capita, which in turn is a positive function of both agricultural productivity A_a and land abundance. 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 $K_m = K - K_a - K_s$).

2.3. *Effects of climate change on factor allocation across sectors*

Direct effects through agricultural productivity. We model climate change as a permanent reduction in local agricultural productivity A_a. Lower agricultural productivity reduces agricultural employment shares of both capital and labor because the comparative advantage of agriculture relative to manufacturing worsens. In addition, it induces a reduction in the employment shares of capital and labor in the service sector because demand for services falls due to lower land income. As a result of these changes, labor and capital reallocate towards manufacturing, whose employment share increases (see Appendix A.2.1 for a proof).

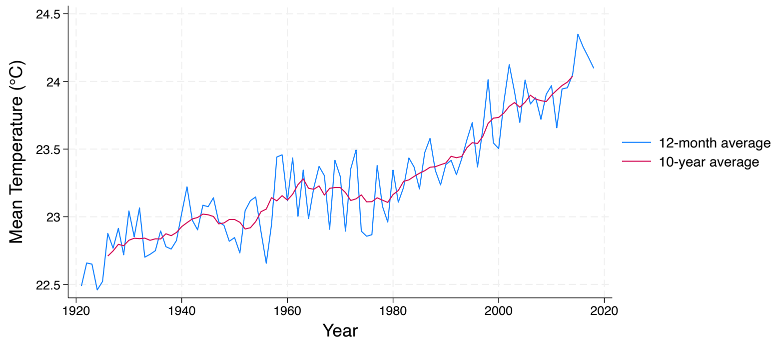
Indirect effects through factor flows. As mentioned above, our empirical findings suggest that climate change can affect regions indirectly through factor reallocation across space in response to permanent agricultural productivity declines in directly affected regions. While our model does not feature 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.2.2 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.2.2 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.2.2 that in equilibrium, the reward to capital increases and all sectors reduce the employment of capital. However, capital use falls faster in manufacturing. Note that in the model, the mechanisms are identical to the ones described above for labor, with an opposite sign.

Appendix Table D1 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 $\hat{K} < 0$).

FIGURE 1.—Average temperature in Brazil since 1920



Notes: Data come from the Climatic Research Unit, University of East Anglia.

3. IDENTIFICATION STRATEGY

3.1. *Meteorological variation in dryness across Brazilian regions*

Brazil's climate has started experiencing several of the effects of global warming. Figure 1 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.[11]

Climate models predict that global warming increases precipitation in high and low latitudes but decreases it in middle ones, which encompass the majority of Brazilian regions (IPCC 2021, page 645). The combination of higher temperature and lower precipitation is expected to lead to an increase in the frequency and duration of droughts in Brazil. This trend has been already documented in the climatology literature (Cunha et al. 2019) and is visible in the time series of natural disasters reported by the National System of Civil Protection or SINPDEC (Sistema Nacional de Proteçao e Defesa Civil). The SINPDEC data is based on reports on natural disasters such as droughts and floods filed by municipal authorities to the federal government, which we digitized for the period 2000 to 2018.[12]

[11] See section 1.4.2 on page 193, Figure TS.23 on page 133 and FAQ 1.3 on page 246 of IPCC (2021).

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

Figure D1 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 D2 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 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.[13] Crucially for our purposes, SPEI measures standard *deviations* of dryness relative to the historical average observed in a given locality.[14] Thus, SPEI has been used by the climatological literature to predict droughts caused by climate change (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.

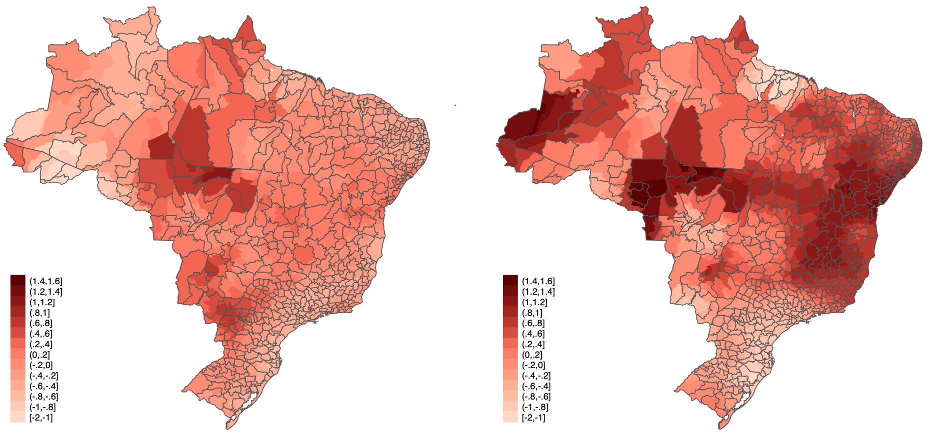
We calculate SPEI as standard deviations in dryness in a given Brazilian municipality in each year within the period 2000 to 2018 relative to the previous century (1901-1999). In the rest of the paper, we define our measure of deviation of dryness relative to historical averages as $\Delta Dryness = SPEI \times -1$, so that an increase in the index captures an increase in excess dryness. In Figure 2, we report the geographical distribution of average $\Delta Dryness$ in the 2001-2010 decade and the 2011-2018 decade. Consistently with the in-

[13]Potential evapotranspiration is defined as the evaporation from an extended surface of an hypotetical 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.

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

FIGURE 2.—Geographical distribution of Excess Dryness

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



Notes: Maps report the average SPEI multiplied by -1 during the indicated time periods with the borders of the 558 microregions of Brazil, the level of clustering of standard errors used in the empirical analysis.

crease 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 Appendix Table C1 shows that there is no correlation between excess dryness during the 2001-2010 period and a set of baseline municipality characteristics.[15] Instead, the frequency of reported droughts in the SINPDEC data tends to be higher in poorer municipalities, as shown in Panel A of Appendix Table C1.[16]

Finally, Figure D3 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

[15]A 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 dryness is also uncorrelated with cumulative deforestation experienced between 2001 and 2010.

[16]In 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.

appears to be drawn from a warmer distribution in the second decade. This is consistent with the trend reported in Figure D1, which shows an increase in the frequency of droughts across Brazilian regions during the last ten years relative to the previous decade. Figure D3 also reports the median (black line) and 90^{th} 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 90^{th} percentile of excess dryness, which corresponds to about 1 standard deviation in the 2000-2010 decade, and to 1.36 standard deviations in the 2011-2018 decade.

In the following, we present the two main specifications we estimate. The first aims at capturing 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.

3.2. *Yearly panel specification*

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

$$y_{mt} = \alpha_m + \alpha_{rt} + \beta_1 \underbrace{\Delta Dryness_{mt}}_{\text{Direct effect}} + \beta_2^K \underbrace{Exposure_{mt}^K}_{\text{Indirect effect}} + \Lambda_t X_{m,t=1991} + u_{mt} \tag{1}$$

Where m indexes municipalities, r indexes one of the five macro-region of Brazil, and t indexes years.[17] 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. $\Delta Dryness_{mt}$ measures changes in dryness relative to the mean level of dryness in a given municipality between 1901 and 1999. This is defined using the climatological dryness index SPEI as described in section 3.1. $Exposure_{mt}^K$ 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 markets. We describe this measure of market integration in

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

detail in section 3.4. $X_{m,t=1991}$ 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 C1 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.

3.3. *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:

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

The outcome variable $\Delta y_{m,2000-2010}$ captures decadal variation in the outcomes of interest at municipality level between 2000 and 2010, which are the last two waves 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 mean level of dryness over the last century as described in section 3.1. As in equation (1), $Exposure^f_{m,2001-2010}$ 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. The superscript $f = K, L$ indicates the type of market integration.[18]

[18]We include exposure via labor markets in the long-differences specification, but not in the yearly panel specification as labor market outcomes are observable at decadal frequency in the Census.

Estimation of direct effects in equation (2) follows a similar strategy as 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 C1 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 (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. However, excess dryness is uncorrelated with deforestation of the Amazon rain forest (Table C1, B). In addition, in the empirical analysis, we control for measures of technical change in soy and maize – the main crops farmed in Brazil, which 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 2, 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 shocks, 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 microregions, namely mesoregions (115 regions). Third, we control for 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.

3.4. *Measures of indirect exposure to excess dryness*

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:

$$Exposure^{K}_{mt} = \sum_{b \in B_m} w_{bm} BankExposure_{bt}, \tag{4}$$

where w_{bm} captures the lending market share of bank b in m and are constructed as the value of loans issued by branches of bank b in m divided by the total value of loans issued by branches of all banks operating in m (whose set we indicate with B_m) in the baseline year 2000. The weighting captures 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 shift-share research designs which 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.[19] As shown in section 3.1, 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 during the 2001 to 2010 period.

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 of previous migrants from their same origin because social networks reduce migration costs

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

(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

$$Exposure^{L}_{mt} = \sum_{o \neq m} \alpha_{om} \Delta Dryness_{ot} \quad \text{with } \alpha_{om} = \frac{M_{1995-2000,o \to m}}{M_{m,2000}},$$

where o denotes the origin municipality, m the destination municipality, $M_{1995-2000,o \to m}$ the size of the migrant flow from o to m between 1995 and 2000, and $M_{m,2000}$ the total number of individuals that migrated during this period to m. 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 decisions. 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 based on data from the previous Population Census. 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 C1).

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, we show that the direct effect of dryness is to generate labor outflows from directly affected regions and labor inflows into indirectly affected regions through migration. This is exactly what we would expect in classic migration models with regional income shocks.

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° (55km $\times$ 55km). Thus, this exclusion insures that our measures of indirect exposure do not capture the effect of dryness recorded in other municipalities located within the same SPEI grid cell. 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. 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 D2, 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 goods market access measure. 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. (2019). 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, θ is the trade elasticity, and $\Delta Dryness_{ot}$ is our measure of the regional shock.[20]

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 marker 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.

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. These data contain information on all formal workers in Brazil, allowing us to follow each worker over time across firms, sectors and locations.[21]

[20] The 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. 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).

[21] Employers are required by law to provide detailed worker information to the Ministry of Labor. See Decree n. 76.900, December 23^{rd} 1975. Failure to report can result in fines. RAIS is used by the Brazilian Ministry of Labor to identify workers entitled to unemployment benefits (*Seguro Desemprego*) and federal wage supplement

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:

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

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 3.4. 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:

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

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 that occurred in the origin between 2006 and 2010. To make the estimation computationally

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).

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.[22] 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.

4. RESULTS

4.1. *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, 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.

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

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 C2. 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. Appendix Figure D4 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 C2, 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.

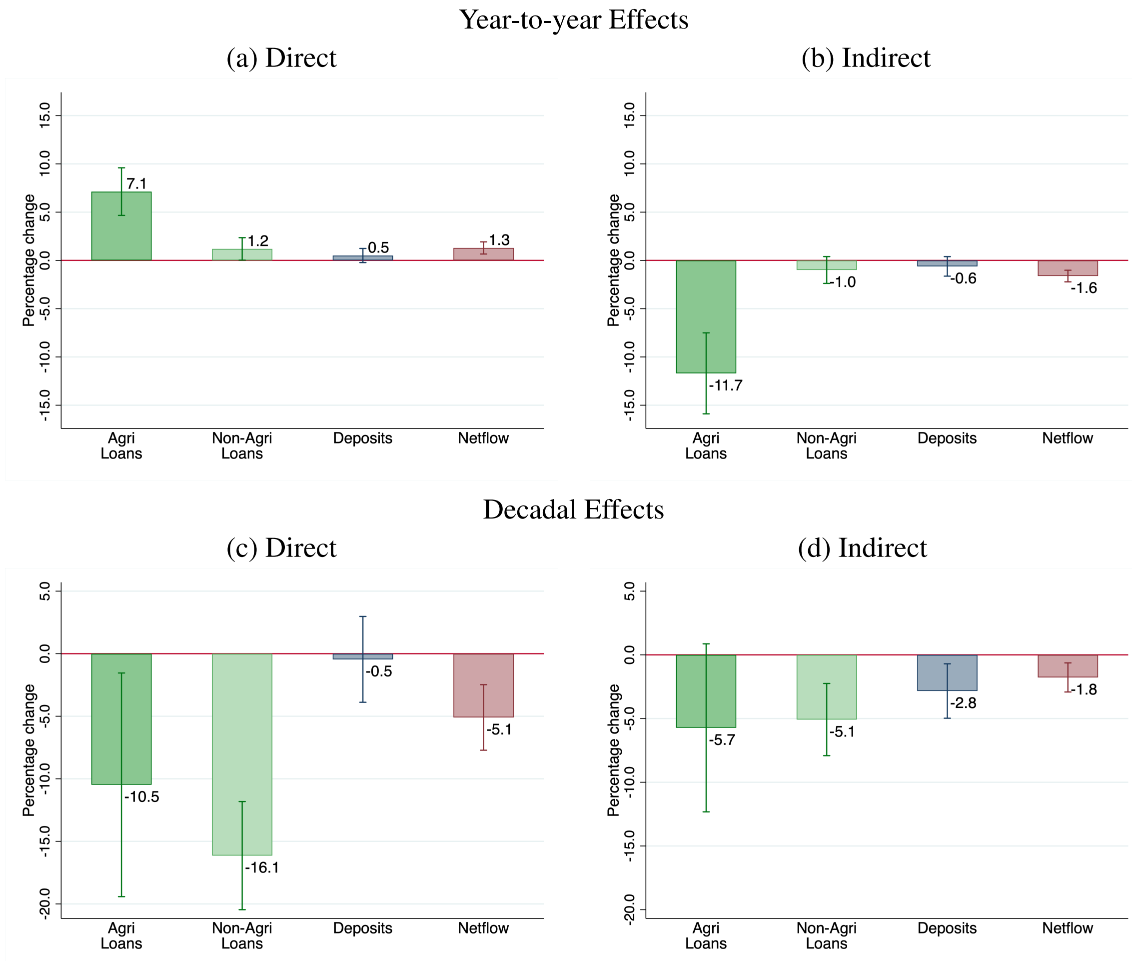
4.2. *The effects of excess dryness on capital allocation*

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.[23] 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 3 (a) and (b), and reported in detail in Table C3. 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 3 (a)]. In turn, regions indirectly connected through the bank network to areas suffering droughts experience capital outflows and a reduction in loans [Figure 3 (b)]. Overall, this suggests 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

[23]Loans and deposits of both firms and individuals are reported together in the ESTBAN data. This has the advantage of including loans to individual farmers running their farms and the disadvantage of pooling together production and consumption loans.

FIGURE 3.—Effects of Excess Dryness on Loans, Deposits and Capital Flows: Yearly vs Decadal Effects



Notes: The figure reports the estimated effects 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. 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. 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. Full regression results are reported in Appendix Tables C3 and C4.

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 C3 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 lending, which is concentrated in agricultural loans.[24]

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 4.3.

The results are summarized in Figure 3 (c) and (d) and reported in detail in Table C4. 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,

[24] Notice 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 to keep their exposure to the agricultural sector at the mandated minimum.

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 2 and its predictions summarized in Table D1. In directly affected regions, the model predicts that a reduction in agricultural productivity reallocates capital away from agriculture and services into manufacturing. This can explain the sharp reduction in agricultural loans observed in the data. However, we also see a large reduction in lending to non-agriculture. This result implies that manufacturing is not absorbing the credit released by the agricultural sector. There are two potential reasons for this result. Manufacturing might display some degree of decreasing returns to scale so that the equilibrium return to capital falls in the region. This would generate capital outflows towards other regions. However, we do not observe capital inflows into regions financially connected to areas experiencing an increase in dryness. On the contrary, we observe capital outflows from those regions. Then, a neoclassical framework cannot 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 (Aguilar-Gomez et al. 2022). If there are frictions in the interbank market, those banks might reduce lending everywhere, also in regions not affected by excess dryness. 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 D1, 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 C4. It is also consistent with the findings documented in Table C6, 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 in response 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 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.

4.3. *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 I. 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

TABLE I

DECADAL EFFECT OF DRYNESS ON EMPLOYMENT (2000-2010)

Outcomes:	Δlog Employment			
	(1)	(2)	(3)	(4)
$\Delta\text{Dryness}_{2001-2010}$	-0.0124**	-0.0250***	-0.0246***	-0.0255***
	(0.00590)	(0.00664)	(0.00703)	(0.00779)
Exposure to Dryness via migrants		0.0219***	0.0218***	0.0217***
		(0.00578)	(0.00588)	(0.00588)
Exposure to Dryness via banks			-0.0120***	-0.0119***
			(0.00424)	(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.

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. Estimates are remarkably stable to adding controls for initial municipality characteristics in column (3), and the exposure to dryness via banks in column (4), which lends support to the identification assumptions discussed above.

Regions connected to drying areas 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 C4. Thus, we find that excess dryness generates negative spillovers on financially connected regions which experience reductions in both loans and employment. We discuss the effects on employment in more detail below when decomposing it by sector. In the last column of Table I, we control for a measure of indirect exposure to excess dryness through goods market access, which is based on road travel distance as described in section 3.4. Estimates remain virtually unchanged and its coefficient is small and insignificant. This finding is consistent with the hypothesis that because the main agricultural crops are exported, their prices are determined in the international market. Thus, there are no spillover effects of changes in agricultural good supply in nearby municipalities. [25]

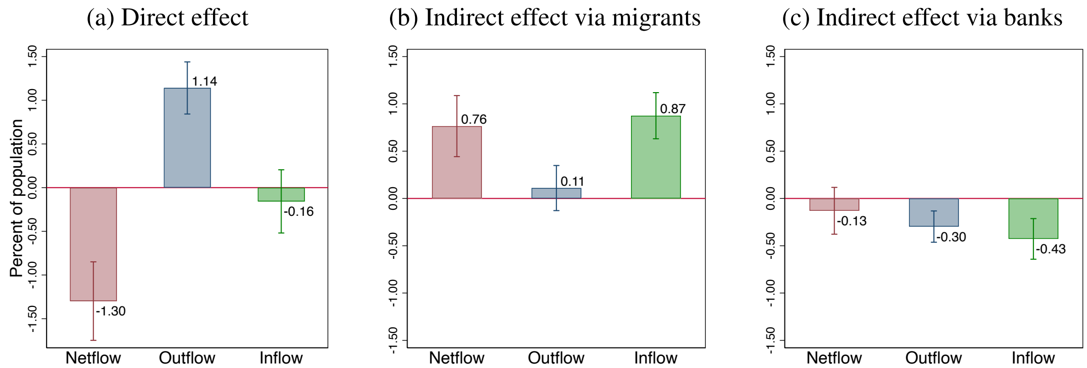
Migration. We shed light on the mechanisms behind the results on employment by investigating the direct and indirect effects of excess dryness on migration flows across municipalities. Census respondents report information on their municipality of residence five years prior to the 2010 Census year. We use this information to construct bilateral migration flows across each municipality pair between 2005 to 2010. We compute the rate of net migrant flows as the difference between the numbers of inflowing and outflowing migrants in 2005-2010 divided by 2010 population. 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.

Findings on migration flow rates are summarized in Figure 4, while detailed regression results are reported in Table C5. 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 realloca-

[25] We report direct and indirect effects of excess dryness on average wages in Appendix Table D3, 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.

[26] Appendix Figure D5 shows that estimates of direct and indirect effects of dryness on net migration flows are stable in terms of magnitude when we exclude smaller or larger areas around each municipality.

FIGURE 4.—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. Full regression results are reported in Appendix Table C5.

tion of workers from directly affected regions to regions that are connected via pre-existing migration networks.[27]

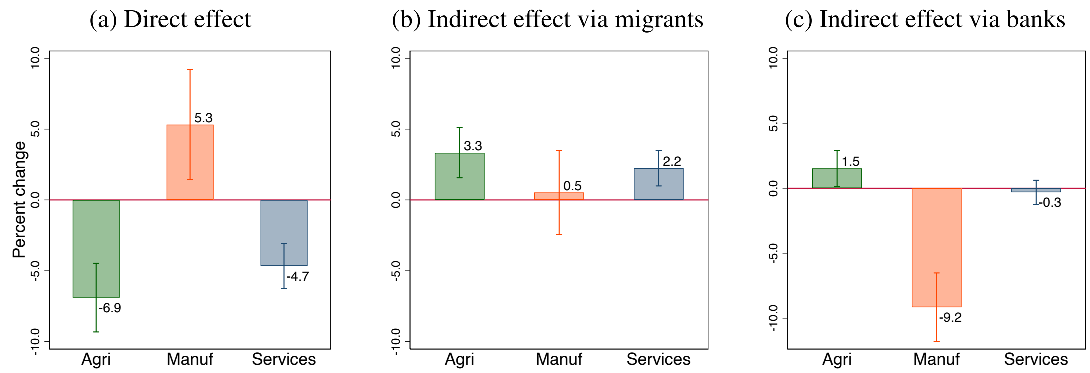
Exposure via banks has no explaining power on net migration flows (Figure 4). This is because *both* outflows and inflows are lower in municipalities with higher exposure to dryness via banks. Taken together, findings suggest that is that the contraction of credit in regions financially connected to drying areas reduce their attractiveness for immigrants by reducing employment opportunities and at the same time hinders (potentially costly) outmigration by tightening credit constraints.

Sectoral Structure of the Economy. The benchmark model presented in Section 2 predicts that a permanent reduction in agricultural productivity in a region will generate a reallocation of labor away from agriculture and services towards manufacturing in both directly affected regions and regions connected via labor markets.

The estimates of the direct and indirect effects of excess dryness on the allocation of labor across sectors are summarized in Figure 5 and reported in detail in Table C6. The results

[27]Consistent with the documented effects on net migration flows, Table D3 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.

FIGURE 5.—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. Full regression results are reported in Appendix Table C6.

on the direct effects across sectors are in line with the predictions of our model reported in the first row of Table D1. 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 around 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 our estimates.

Focusing on the indirect effects through migrant networks, 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 2, the manufacturing sector should increase in relative terms both in regions directly affected and in regions indirectly affected by excess dryness. This asymmetry in the ability of manufacturing to absorb workers across regions could be driven by a mismatch between the skills of climate migrants and the skills required for employment in manufacturing in major destination regions. Alternatively, this finding could also be driven by the fact that migrants' social networks are disconnected from manufacturing firms at destination. This asymmetry in labor market frictions across sectors would result in labor misallocation. We turn to explore these two potential explanations next.

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

To investigate this mechanism, we categorize workers into two skill types based on their level of education reported in the Population Census. We define high-skill workers as those that have at least completed high-school, i.e. have 12 years of education. Table D7 reports the results on the direct and indirect effects of excess dryness on the allocation of labor across sectors separately for low-skill workers (Panel A) and high-skill workers (Panel B).

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

Estimation of indirect effects using employer-employee data. We use social security data for two purposes. First, we construct 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. This interpretation is based on the predictions of economic geography models where bilateral migration flows are a function of bilateral migration costs (Berkes, Gaetani, and Mestieri 2022; Borusyak et al. 2023). Second, we implement the identification strategy described in section 3.4, which exploits variation in climate-driven inflows of migrant workers across firms in the same destination municipality.

We start by exploring to what extent the connections via past 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 in the baseline period and a dummy capturing regions more exposed to excess dryness in the 2006-2010 period. Figure D6 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 had, in the baseline period, 6 percent of workers coming from regions that would experience high excess dryness in the subsequent period (2006-2010). This is about three times the share for firms in the manufacturing sector (2 percent), while the average share for firms in services is in between (4 percent). In short: agriculture has the highest initial labor market connection to areas more affected by excess dryness, while manufacturing has the lowest. These asymmetric spatial labor market frictions suggest a potential explanation for the lack of reallocation of climate migrants into manufacturing in indirectly affected regions.[28]

[28] A potential concern with the stylized fact presented in Figure D6 (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 D7, 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 D7 shows that the stylized fact presented in Figure D6 (a) applies to both formal and informal workers.

Notice that because the geographical distribution of excess dryness is as-good-as-randomly assigned across Brazilian municipalities, the lower connection of manufacturing firms to drying areas suggests that they are in general less connected to any region. This is because manufacturing firms are geographically clustered and tend to source their employees locally. Figure D8, shows the geographical distribution of the employment share of each sector across Brazilian municipalities. Despite the fact that agriculture and manufacturing 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. [29]

Next, we implement a firm-level version of our empirical strategy to estimate the indirect effects of dryness through migrant networks. The objective of this analysis is to compare firms in the same destination municipality differently exposed to climate migrants through their initial employment connections to drying municipalities. This permits to isolate the role of labor market integration relative to goods and capital market integration. In addition, it permits to directly quantify the role of asymmetric spatial labor market frictions on the lack of labor reallocation towards manufacturing in destination municipalities.

Table C7 reports the results of estimating equation (6). 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.

[29] In Figure D9, we also 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.

In column (2), we include the interaction term between the connection to a certain origin and a dummy capturing whether the origin experienced high excess dryness. The point estimates of both β_1 and β_2 are positive and 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 2006-2010.

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.

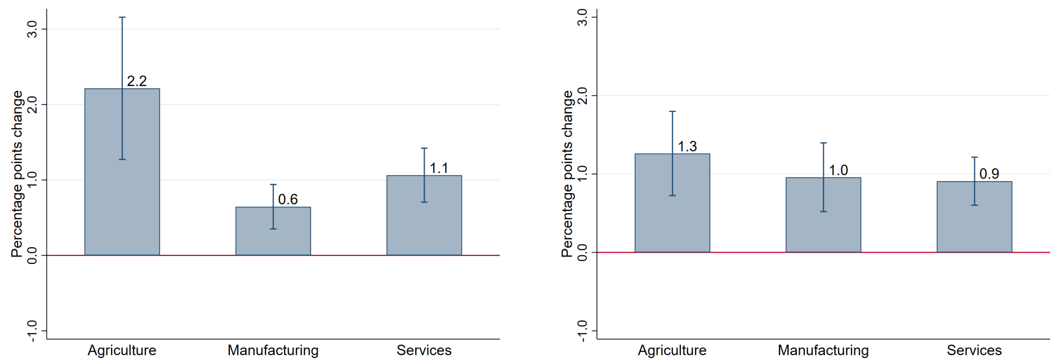
In columns (4)-(6) we split our sample by sector. The differential increase in worker flows from areas with high excess dryness is relatively similar across sectors, with larger coefficients for agriculture than manufacturing and services. As documented in Figure D6, agricultural firms tend to be on average more connected to affected areas via their past workers' flows. As shown in Figure 6 (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.This effect is two to three times greater than the one observed for firms in services (1.1) and manufacturing (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 6 (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

FIGURE 6.—Firm exposure and employment growth

(a) Sector-specific spatial frictions

(b) Counterfactual with symmetric spatial frictions across sectors



Notes: Panel (a) reports the effect of $Dryness$ on employment growth for firms with the average connection to areas with excess dryness observed in their sector, computed by multiplying this average with the estimated coefficient β_2 in column (4) of Table C7. 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.

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 2.

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

Overall, these results are consistent with the existence of frictions driving the reallocation of workers displaced by permanent increases in dryness in the Brazilian labor market. First, the results indicate that climate-driven labor reallocation can retard structural transformation in destination regions. Largely due to assymetric spatial frictions, displaced workers tend to be absorbed at a higher rate in agriculture than in manufacturing. Second, the impact of pre-existing connections on employment flows is larger for small firms.

5. 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 capital outflows consistent with a permanent decrease in investment opportunities. We also find that persistent 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 flows. Overall, the combination of large long-run effects on agricultural production and outflows of labor and capital suggests limited scope for local adaptation responses.

We also document spillovers on regions connected to areas experiencing droughts through factor markets. First, financially integrated areas experience a reduction in lending which hurts manufacturing employment. Second, 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. These spatial spillovers generate de-industrialization and increase the weight of small firms in the firm size distribution of destination regions. The lack of factor reallocation into manufacturing is not optimal from the point of view of our model because agriculture faces decreasing returns to scale as land is in fixed supply.

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

APPENDIX A: MODEL DERIVATIONS

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

$$Y_a = A_a T^{\beta} \left(K_a^{\gamma} L_a^{1-\gamma}\right)^{1-\beta} \tag{A1}$$

$$Y_m = A_m K_m^{\gamma} L_m^{1-\gamma} \tag{A2}$$

$$Y_s = A_s K_s^{\gamma} L_s^{1-\gamma} \tag{A3}$$

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

A.1. *Equilibrium*

A.1.1. *Factor prices*

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

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

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

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

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

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

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

A.1.2. *Equilibrium factor allocation across sectors*

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

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

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

Agriculture Profit maximization in agriculture implies

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

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

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

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

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

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

A.1.2.0.1. *Services* Aggregate demand for services is

$$P_sC_s = \alpha_s\left(wL + r_kK + r_TT\right)$$

where α_s is the consumption expenditure share on services.

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

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

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

Manufacturing Labor and capital factor market clearing imply:

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

which together with (A5) yields:

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

A.2. *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.2.1. *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.2.2. *Indirect effect at destination*

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

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

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

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

Agriculture employment levels L_a and K_a:

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

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

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

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

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

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

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

Service employment levels L_s and K_s:

First, we differentiate equation (A9):

$\hat{X}_s = \alpha_s \frac{X}{X_s}\hat{X}$.

$\hat{X}_s - \hat{X} = \left(\alpha_s \frac{X}{X_s} - 1\right)\hat{X}$.

Therefore, using (A5), have

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

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

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

those for labor above imply that labor flows into services and capital leaves the sector, less than proportionally to the reduction in capital supply.

Manufacturing employment levels L_m and K_m:

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

APPENDIX B: EXCESS DRYNESS AND REPORTED DROUGHTS

Although reported droughts cannot be used for identification because of endogeneity concerns (Panel A of Table C1 and discussion in section 3.1), 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:

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

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.

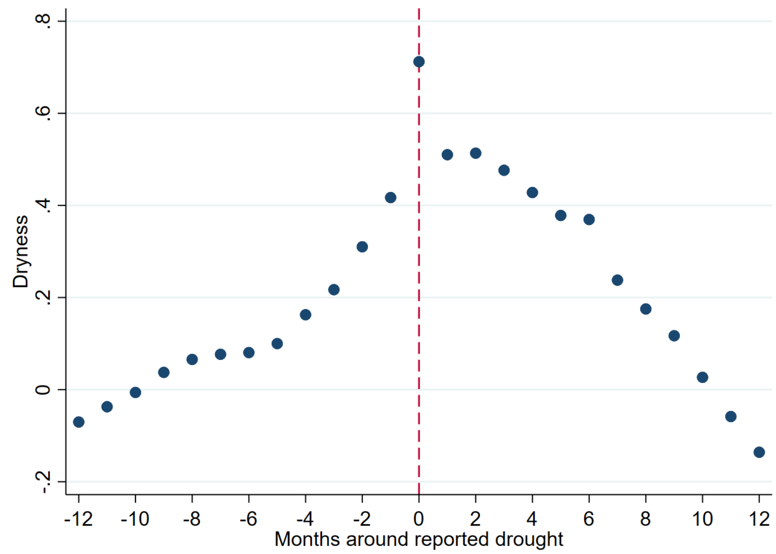
Figure B1 plots the coefficients β_k. As shown, the deviation of $Dryness$ from its mean is the highest in the month a drought is reported, around 0.7 standard deviations above the long run average dryness of that location. The figure also shows that dry weather is registered well ahead of the month 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:

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

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

FIGURE B1.—Average excess dryness index around drought events



Notes: The figure shows the β_k coefficients of the 12 leads and 12 lags of the $drought$ dummies estimated based on equation B1 and using monthly data at the municipality level from 2000 to 2018.

specifications include macro-region (r) fixed effects interacted with year fixed effects, as well as the initial municipality controls used in Table C1 (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.

TABLE B1

REPORTED DROUGHTS AND EXCESS DRYNESS

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

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

APPENDIX C: MAIN TABLES

TABLE C1

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: Excess Dryness

	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 C2

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)
ΔDryness	-0.0825***	-0.0820***	-0.0821***	-0.0808***
	(0.0127)	(0.0126)	(0.0140)	(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)
ΔDryness$_{2001-2010}$	-0.0950*	-0.152***	-0.176***	-0.237***
	(0.0516)	(0.0527)	(0.0579)	(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 C3

YEAR-TO-YEAR EFFECTS OF EXCESS DRYNESS ON CAPITAL OUTCOMES
2000-2018

Outcomes:	log loans					log deposits	net flows
	all	all	all	agri	non-agri		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔDryness	0.0382***	0.0450***	0.0341***	0.0714***	0.0131*	0.00593	0.0135***
	(0.00705)	(0.00749)	(0.00714)	(0.0149)	(0.00700)	(0.00440)	(0.00381)
Exposure to Dryness via banks		-0.0299***	-0.0337***	-0.117***	-0.0102	-0.00620	-0.0164***
		(0.0105)	(0.0100)	(0.0255)	(0.00844)	(0.00615)	(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 C4

DECADAL EFFECT OF DRYNESS ON CAPITAL OUTCOMES (2000-2010)

Outcomes:	Δlog loans					Δlog deposits	Δnet flows
	all	all	all	agri	non-agri		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta\text{Dryness}_{2001-2010}$	-0.151***	-0.150***	-0.159***	-0.105*	-0.161***	-0.00455	-0.0510***
	(0.0233)	(0.0238)	(0.0280)	(0.0542)	(0.0262)	(0.0208)	(0.0159)
Exposure to Dryness via banks		-0.0475**	-0.0729***	-0.0573	-0.0508***	-0.0284**	-0.0177**
		(0.0186)	(0.0170)	(0.0400)	(0.0172)	(0.0130)	(0.00693)
Exposure to Dryness via migrants			0.102***	0.0723	0.142***	0.0213	0.0294**
			(0.0260)	(0.0535)	(0.0224)	(0.0175)	(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 C5

MIGRATION FLOWS (2005-2010)

Outcomes:	net migration flows			outflows	inflows
	(1)	(2)	(3)	(4)	(5)
ΔDryness$_{2001-2010}$	-0.00835***	-0.0129***	-0.0130***	0.0114***	-0.00157
	(0.00235)	(0.00275)	(0.00273)	(0.00181)	(0.00220)
Exposure to Dryness via migrants		0.00746***	0.00765***	0.00110	0.00875***
		(0.00197)	(0.00196)	(0.00145)	(0.00148)
Exposure to Dryness via banks			-0.00130	-0.00297***	-0.00428***
			(0.00150)	(0.00100)	(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. Outflows and inflows are defined as the number of outgoing and incoming migrants, respectively, divided by municipality population. Net migration flows are the difference between inflows and outflows. 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 C6

DECADAL EFFECT OF DRYNESS ON EMPLOYMENT BY SECTOR (2000-2010)

Outcomes:	Δlog Employment		
	agri	manuf	serv
	(1)	(2)	(3)
ΔDryness$_{2001-2010}$	-0.0689***	0.0532**	-0.0466***
	(0.0147)	(0.0235)	(0.00968)
Exposure to Dryness via migrants	0.0333***	0.00524	0.0224***
	(0.0107)	(0.0179)	(0.00759)
Exposure to Dryness via banks	0.0152*	-0.0916***	-0.00314
	(0.00834)	(0.0160)	(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 C7

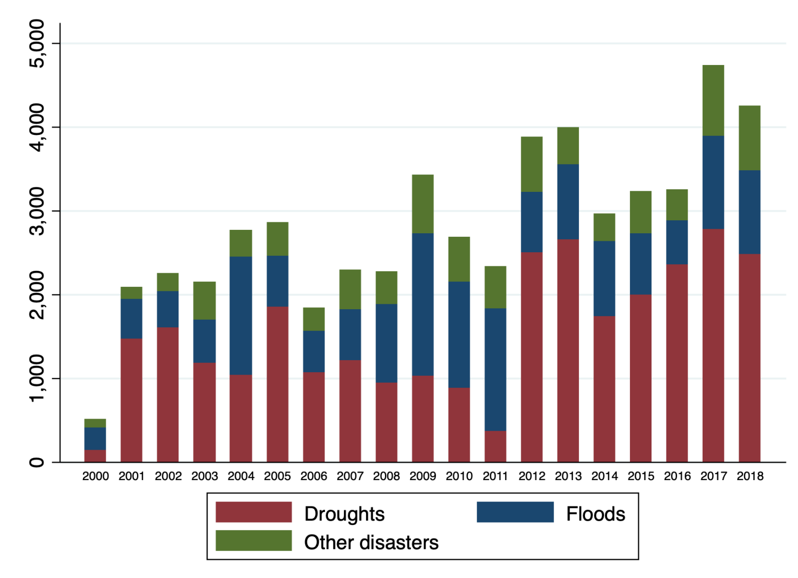
WORKERS' FLOWS TO FIRMS EXPOSED TO DRYNESS

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

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

APPENDIX D: ADDITIONAL FIGURES AND TABLES

FIGURE D1.—Reported Natural Disasters By Year: 2000-2018

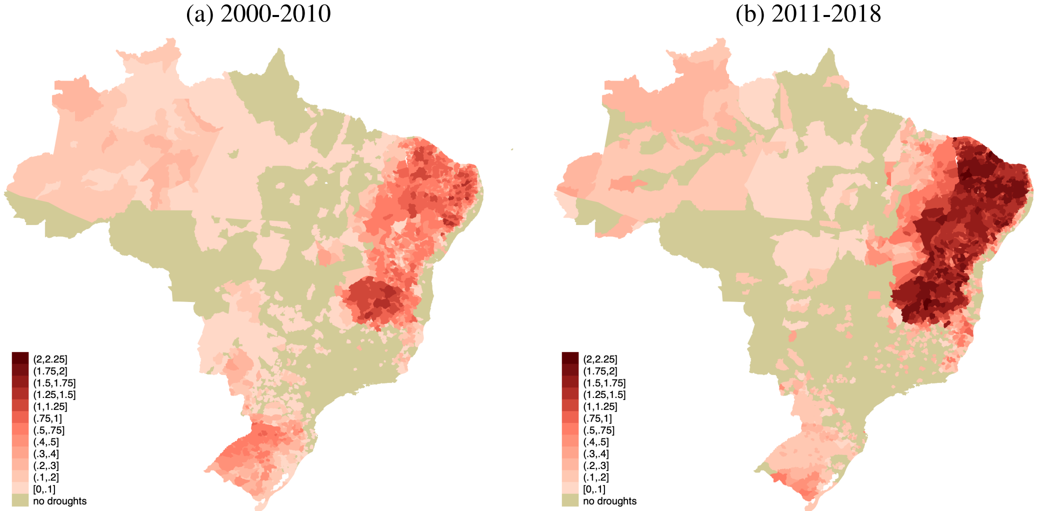


Source: Sistema Nacional de Proteçao e Defesa Civil - SINPDEC

FIGURE D2.—Geographical distribution of reported droughts

Reported droughts

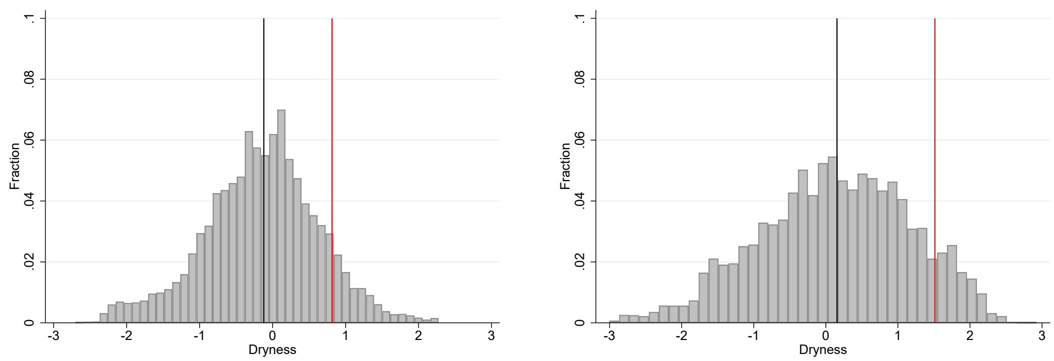
(a) 2000-2010 (b) 2011-2018



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

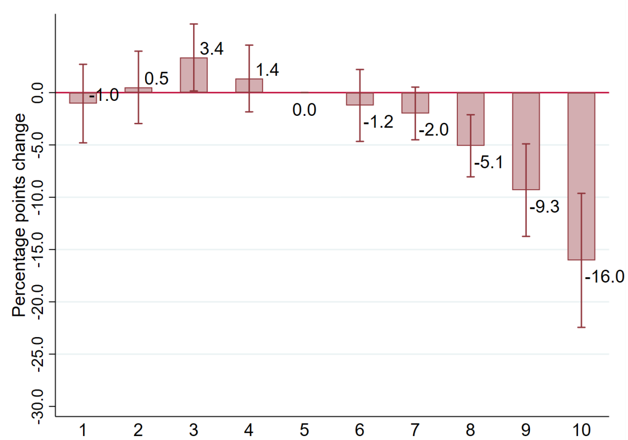
FIGURE D3.—Distribution of Excess Dryness Index Across Municipalities

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



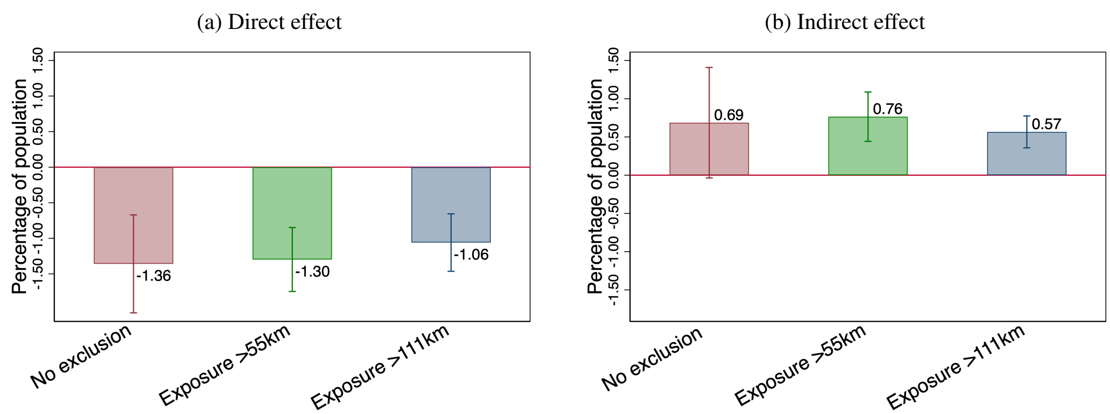
Notes: The figure shows the distribution of $Dryness$ (SPEI$\times -1$) across Brazilian municipalities by decade. The black line in both graphs represents the 50^{th} percentile of the distribution, while the red line in both graphs represents the 90^{th} percentile of the distribution. Quantifications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

FIGURE D4.—Effects of Excess Dryness on Value of Production in Agriculture By Decile of Dryness



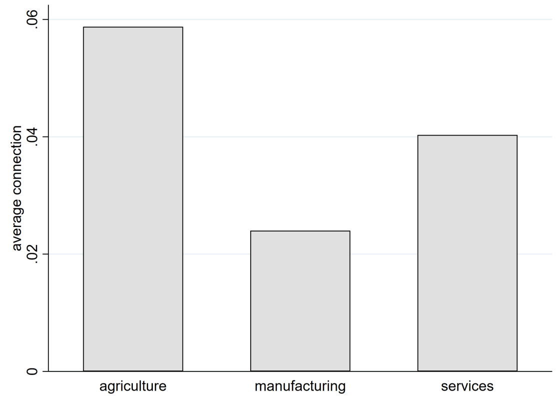
Notes: The figure shows the coefficients on dummies capturing deciles of the excess dryness index in a panel regression at municipality-year level for 2000-2010. the outcome variable is the log value of agricultural production for the top 10 crops in Brazil as recorded in the PAM survey. Deciles of $Dryness$ go from wettest to driest. Estimated effects are relative to the 5^{th} decile. Controls include AMC FE, macroregion-year FE, 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 D5.—Effects of Excess Dryness on the net migration rate



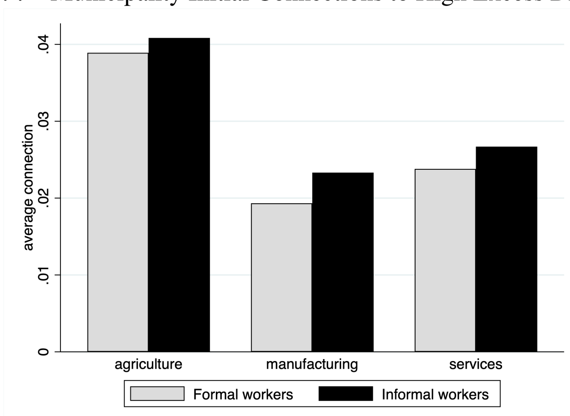
Notes: The figure reports the estimated effects on the net migration flow relative to population during the 2005-2010 for a municipality going from the 50th to the 90th percentile in the direct and indirect (exposure via migrant network) measures of excess dryness. We report the estimated coefficients 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 D6.—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.

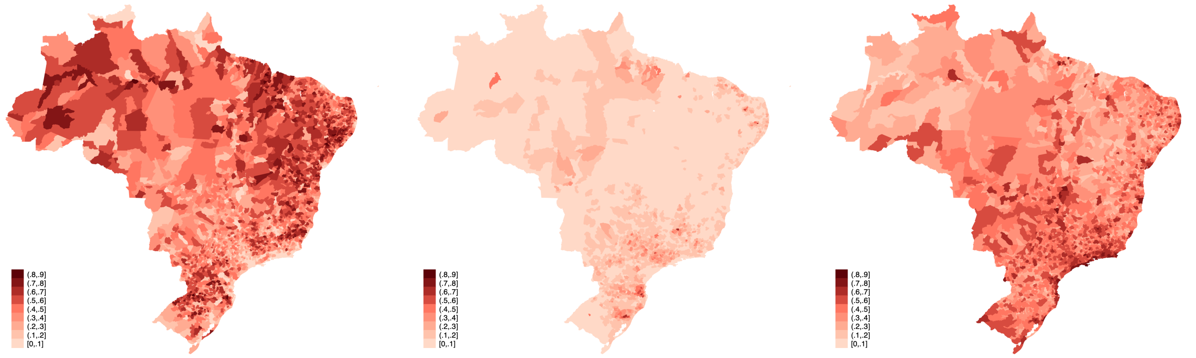
FIGURE D7.—Municipality Initial Connections to High Excess Dryness Areas



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.

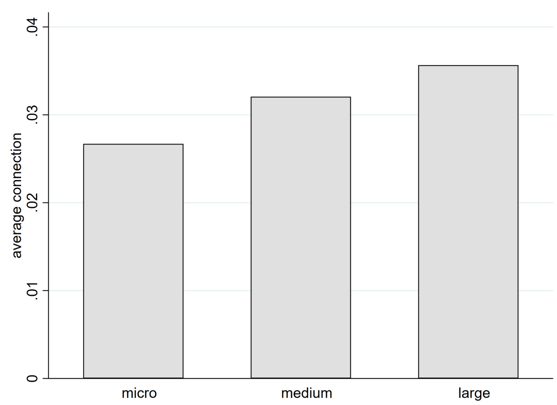
FIGURE D8.—Geographical distribution of sectoral employment shares

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



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

FIGURE D9.—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 D1

MODEL PREDICTIONS

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

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

TABLE D2

CORRELATION BETWEEN MEASURES OF EXPOSURE

	ΔDryness	Exposure via banks	Exposure via migrants
ΔDryness	1.000		
Exposure via banks	0.110	1.000	
	0.000		
Exposure via migrants	0.643	0.157	1.000
	0.000	0.000	

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

TABLE D3

DECADAL EFFECT OF DRYNESS ON POPULATION AND WAGES
2000-2010

Outcomes:	Δlog Pop		Δlog wage	
	(1)	(2)	(3)	(4)
ΔDryness$_{2001-2010}$	-0.0484***	-0.0490***	0.0115	0.0120
	(0.00654)	(0.00648)	(0.00775)	(0.00787)
Exposure to Dryness via migrants	0.0229***	0.0242***	0.0118*	0.0106
	(0.00442)	(0.00442)	(0.00657)	(0.00673)
Exposure to Dryness via banks		-0.00928***		0.00678
		(0.00335)		(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 D4

ROBUSTNESS OF CAPITAL EFFECTS TO CLUSTERING AT MESOREGION LEVEL

Panel A: Yearly Effects

Outcomes:	log loans					log deposits	net flows
	all	all	all	agri	non-agri		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔDryness	0.0382***	0.0450***	0.0341***	0.0714***	0.0131	0.00593	0.0135***
	(0.0102)	(0.0114)	(0.00795)	(0.0190)	(0.00897)	(0.00746)	(0.00423)
Exposure to Dryness via banks		-0.0299*	-0.0337**	-0.117***	-0.0102	-0.00620	-0.0164***
		(0.0168)	(0.0159)	(0.0391)	(0.0129)	(0.00955)	(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:	Δlog loans					Δlog deposits	Δnet flows
	all	all	all	agri	non-agri		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔDryness$_{2001-2010}$	-0.151***	-0.150***	-0.159***	-0.105	-0.161***	-0.00455	-0.0510**
	(0.0322)	(0.0345)	(0.0361)	(0.0708)	(0.0313)	(0.0266)	(0.0208)
Exposure to Dryness via banks		-0.0475	-0.0729***	-0.0573	-0.0508*	-0.0284	-0.0177
		(0.0298)	(0.0244)	(0.0663)	(0.0279)	(0.0242)	(0.0112)
Exposure to Dryness via migrants			0.102***	0.0723	0.142***	0.0213	0.0294*
			(0.0296)	(0.0620)	(0.0271)	(0.0231)	(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 D5

ROBUSTNESS OF EMPLOYMENT AND MIGRATION EFFECTS TO CLUSTERING AT MESOREGION LEVEL

Outcomes:	Δlog Employment				netflows	outflows	inflows
	all	agri	manuf	serv			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔDryness$_{2001-2010}$	-0.0255***	-0.0689***	0.0532*	-0.0466***	-0.0130***	0.0114***	-0.00157
	(0.00862)	(0.0195)	(0.0310)	(0.0135)	(0.00345)	(0.00258)	(0.00313)
Exposure to Dryness via migrants	0.0217***	0.0333**	0.00524	0.0224***	0.00765***	0.00110	0.00875***
	(0.00593)	(0.0143)	(0.0188)	(0.00769)	(0.00226)	(0.00191)	(0.00158)
Exposure to Dryness via banks	-0.0119**	0.0152	-0.0916***	-0.00314	-0.00130	-0.00297**	-0.00428**
	(0.00548)	(0.0104)	(0.0218)	(0.00769)	(0.00183)	(0.00115)	(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 D6

ROBUSTNESS OF POPULATION AND WAGE EFFECTS TO CLUSTERING AT MESOREGION LEVEL

Outcomes:	Δlog Pop		Δlog wage	
	(1)	(2)	(3)	(4)
ΔDryness$_{2001-2010}$	-0.0484***	-0.0490***	0.0115	0.0120
	(0.00980)	(0.00941)	(0.0115)	(0.0119)
Exposure to Dryness via migrants	0.0229***	0.0242***	0.0118	0.0106
	(0.00487)	(0.00479)	(0.00842)	(0.00869)
Exposure to Dryness via banks		-0.00928*		0.00678
		(0.00487)		(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.

TABLE D7

DECADAL EFFECT OF DRYNESS ON EMPLOYMENT BY SECTOR AND SKILL LEVEL
2000-2010

Panel A: Low-skill workers

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

Panel B: High-skill workers

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

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