

Climate Change and the Spatial Reallocation of Capital*

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Abstract

Climate change is expected to increase drought conditions in many developing countries, leading to large agricultural productivity losses. Standard trade and geography models predict that the optimal adaptation response is a reallocation of economic activity away from affected regions towards other areas with higher returns. We study the effects of recent changes in climate in Brazil to understand to what extent labor and credit market frictions shape this reallocation process. We develop a spatial equilibrium model where banks reallocate credit across regions through their branch networks and workers can migrate. While persistent increases in dryness generate migration outflows from affected areas towards other regions, credit reallocation follows a different pattern. In the short run, banks provide insurance to drought-affected regions by channeling capital inflows from connected areas. When increases in dryness become persistent, loan defaults reduce bank liquidity and generate credit contractions throughout branch networks. This credit disruption channel propagates agricultural shocks to regions not directly affected by climate change.

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

JEL codes: O1, Q54, O16, J61.

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I INTRODUCTION

Global warming is expected to reduce precipitation in subtropical regions, leading to large agricultural productivity losses (IPCC 2021). A key question for understanding the economic costs of climate change is how labor and capital reallocate across space in response to these productivity shocks. Classic models predict that factors should flow away from affected regions toward areas with higher returns (Corden and Neary, 1982; Matsuyama, 1992; Krugman, 1991). However, spatial frictions in labor and capital markets may constrain this adjustment process (Goldberg and Pavcnik, 2007; Buera et al., 2011; Gollin et al., 2014; Munshi, 2020; Porzio et al., 2022; Donovan and Schoellman, 2023).

In this paper, we develop a spatial equilibrium model that incorporates both bank branch networks and labor migration networks, and use it to guide an empirical analysis of how the effects of climate change propagate across space through these two channels. We test the predictions of the model using data on capital and labor flows across Brazilian regions. Brazil is suited for this analysis because its climate has already started experiencing the effects of global warming. We document an increase in meteorological dryness (combination of lower rainfall and higher temperatures) in the last decades relative to the previous century, as well as an increase in the frequency of droughts reported by municipalities to the federal government using newly digitized administrative data.¹ These changes have important implications for agricultural productivity, and have been largely heterogeneous across Brazilian municipalities, creating variation in local productivity induced by climate that we can exploit to test the predictions of the model.

The objective of the model is to understand how regional productivity shocks induced by climate propagate across space. The model features two key channels of spatial integration: capital flows across regions, intermediated by banks operating a branch network in multiple locations, and labor migration across regions, governed by workers' location choices following pre-existing migrant networks. A distinctive feature of our framework is that firms face a cash-in-advance constraint, i.e. they must borrow from banks to finance a fraction of their wage bill before production takes place. This creates a link between local labor market conditions and credit markets. Banks allocate lending across locations based on expected returns, and when they face liquidity shocks in some locations, these may propagate throughout their branch network.

The model delivers an estimating equation that decomposes the response of local credit and employment to climate shocks into three components: (i) the direct effect of the local productivity shock; (ii) indirect effects via labor market integration, captured by the migration network; and (iii) indirect effects via credit market integration, captured

¹Climate 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).

by the bank branch network matrix. These theoretical predictions guide our empirical specifications and provide an economic interpretation for the reduced-form coefficients we estimate.

We capture changes in regional climate using the Standardized Precipitation and Evapotranspiration Index (SPEI), which measures deviations in drought conditions relative to a 100-year historical average (Vicente-Serrano et al. 2010). We construct measures of indirect exposure to climate shocks through credit markets using the structure of bank branch networks, following Bustos et al. (2020), and through labor markets using past migration flows, following Borusyak et al. (2023).

We begin by documenting that persistent excess dryness causes large reductions in agricultural output. A municipality moving from the median to the 90th percentile of excess dryness experience a decline in the value of agricultural production of more than 20% over the last two decades. Effects are highly non-linear, with sharp reductions in output at the top of the dryness distribution but no significant effects of excess wetness. This confirms that climate shocks generate substantial local productivity losses.

We then study how these effects propagate through bank branch networks. A key finding is that the short-run and long-run effects operate in opposite directions. In the short run, the banking sector provides insurance: regions experiencing droughts receive capital inflows and increased lending, funded by branches in other locations. This is consistent with a consumption smoothing motive, whereby farmers borrow against future income to cope with shocks perceived as temporary. However, this insurance provision exposes banks to climate risk. When drought conditions persist, affected borrowers cannot repay their loans, reducing bank liquidity. Due to frictions in the interbank market, banks then contract lending throughout their branch network.

The long-run results confirm this credit disruption channel. A municipality moving from the median to the 90th percentile of average excess dryness over the 2001-2010 period experienced a 16 percent decline in lending. Regions indirectly connected through bank networks also experienced significant credit contractions, with magnitudes about half the size of the direct effect.

Turning to labor markets, we find that the effects of higher dryness propagate through migration networks in the direction predicted by the model. Regions directly affected by excess dryness experience net outflows of migrants, while regions connected through pre-existing migrant networks experience net inflows. A municipality moving from the median to the 90th percentile of excess dryness experiences a 1.3 percentage points larger net outflow of migrants as a share of population. Conversely, a municipality at the 90th percentile of indirect exposure via migrants experiences a 0.76 percentage points larger net inflow rate.

These migration flows translate into employment effects. Directly affected regions experience a 2.5 percent decline in total employment, while regions connected via migra-

tion networks experience a 2.2 percent increase. Overall, we find that the two channels of spatial integration generate opposite effects on destination employment: the migration network brings workers and expands employment, while the bank network transmits credit shocks and contracts employment.

The combination of model and empirical analysis highlights the following key insights. First, as emphasized by previous literature (Borusyak et al. (2023)) ignoring indirect effects leads to attenuation bias when shocks are spatially correlated. Indeed, we show that the estimated direct effects on both capital and labor increase significantly when we control for spillovers. Second, the short-run insurance mechanism that banks provide generates long-run vulnerabilities when shocks persist. Third, the model shows that indirect capital effects depend critically on how much banks rely on their own branch network versus the interbank market for funding. When shocks persist and borrowers default, banks with limited access to interbank funding contract lending throughout their branch network. Finally, we document that capital adjusts faster than labor: credit contractions in affected regions are an order of magnitude larger than employment effects.

Related Literature

We contribute to the literature studying adaptation to climate change in developing countries. Quantitative spatial models highlight factor reallocation as a key channel of adjustment, with workers and capital moving from directly affected rural regions toward the industrial and service sectors in distant urban areas (Conte et al. 2021; Desmet and Rossi-Hansberg 2015; Nath 2022). However, direct empirical evidence on how climate change affects capital reallocation across regions remains scarce. A rich literature documents risk-sharing mechanisms in rural communities exposed to weather shocks (Townsend 1994; Udry 1994; Fafchamps et al. 1998; Casaburi and Willis 2018), and a few studies examine cross-regional capital flows in response to natural disasters (Yang 2008; Asdrubali et al. 1996). 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.

Our paper is also related to the recent literature studying the effects of climate change on financial institutions. Several studies document that weather-related losses increase loan defaults and reduce credit access (Aguilar-Gomez et al. 2024 for Mexico; De Roux 2021 for Colombia; Bayangos et al. 2021 for the Philippines; Brei et al. 2024 for Caribbean countries). A related strand examines how financial development shapes adaptation to climate shocks (Rajan and Ramcharan 2023 for the US; Burgess et al. 2017 for India; Lane 2024 for Bangladesh). Most recently, Meisenzahl (2024) and Jung et al. (2024) study bank-level exposure to weather shocks and transition risk. Our contribution relative to this literature is to provide a theoretical framework that delivers testable predictions on how climate shocks propagate across space to affect credit supply in regions not directly

hit, and test such predictions using micro-data.

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 a theoretical and empirical framework which takes into account not only local changes in climate but also shocks to other regions integrated through labor and credit markets. Our results show that ignoring indirect effects through spatial networks leads to attenuation of estimated direct effects, as discussed by the literature on estimation of direct and indirect effects of regional shocks (Borusyak et al. 2023; Adao et al. 2019). While this literature has focused primarily on goods and labor market linkages, we study how shocks propagate through capital market linkages, specifically bank branch 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; Adao et al. 2019; Bustos et al. 2020; Fajgelbaum et al. 2021; Imbert et al. 2022; Imbert and Ulyssea 2023). In particular, Allen and Atkin (2022) study how weather shocks propagate across regions through agricultural goods markets in India. We contribute by studying propagation through bank branch networks.

While this paper develops a spatial equilibrium framework that jointly models capital and labor reallocation across space, Albert et al. (2025), our companion paper, focuses on reallocation across sectors. In that paper, we document that persistent dryness generates a large reduction in agricultural employment, with workers in drying regions partially reallocating toward local manufacturing and migrant workers disproportionately being absorbed by small firms outside manufacturing in destination regions. That paper proposes a novel measure of firms' exposure to climate migrants using matched employer-employee data from social security records, and shows that spatial labor market frictions constrain the reallocation from agriculture to the industrial sector.

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 depend critically on the extent to which factor market frictions constrain adjustment. 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).

II A THEORY OF CLIMATE CHANGE AND CREDIT REALLOCATION

II.A MODEL OVERVIEW

We develop a spatial equilibrium model to understand how the effects of climate change propagate across space through credit and labor markets. In our setting, climate shocks affect regional productivity and the total amount of funds banks can lend. The model features two key channels of spatial integration: (i) capital flows across regions, intermediated by banks operating branch networks in multiple locations, and (ii) labor migration across regions, governed by workers' location choices.

The framework builds on the economic geography literature, extending the approach of Borusyak et al. (2023) to incorporate credit market frictions. A distinctive feature of our model is that firms face a *cash-in-advance constraint*: they must borrow from banks to finance a fraction of their wage bill before production takes place. This creates a demand for loans that links local labor market conditions to credit markets. Banks, in turn, allocate their lending across locations based on expected returns, with an idiosyncratic component to returns that generates an upward-sloping supply of capital in each location following a selection logic similar to Kleinman et al. (2023) and Pellegrino et al. (2025).

The model delivers estimating equations that decompose the response of local credit and employment to productivity shocks into three components: (i) *direct effects* that capture the local impact of the shock; (ii) *indirect effects via capital markets* that capture spillovers through bank branch networks; and (iii) *indirect effects via labor markets* that capture spillovers through migration networks. These theoretical predictions guide our empirical specifications and provide an economic interpretation for the reduced-form coefficients we estimate.

Notation Scalars are denoted by italic letters, vectors by bold lowercase letters, and matrices by bold uppercase letters. A hat denotes a log change. For example, w_l is the wage in location l , \mathbf{w} is the vector of wages across locations, and $\hat{\mathbf{w}}$ denotes log changes in wages.

II.B MODEL WITH ONLY CREDIT REALLOCATION

We first present a simplified version of our model that focuses on credit allocation across locations in an environment where there is no labor mobility and financial frictions are extreme: cash-in-advance constraints apply to all expenses they incur. This allows us to highlight the novel elements of our model. We then relax both assumptions and present results for our full model.

Endowments, Production Technologies and Demand Consider an economy with $l \in \{1, \dots, L\}$ locations. Each location is endowed with a fixed supply of labor \bar{L}_l , which we assume is immobile and inelastically supplied to the local labor market l .

Each location produces a differentiated good using labor as the only input. Production in location l is given by:

$$Y_l = A_l L_l, \quad (1)$$

where A_l denotes local productivity and L_l is employment.

We assume that each region in Brazil behaves as a small open economy in an Armington sense: each region produces a differentiated product and world demand is CES with elasticity $\sigma > 1$. We normalize the product of world expenditures times the CES price index (to the power of $\sigma - 1$) to one, so that demand for goods produced in location l satisfies²

$$Y_l = p_l^{-\sigma}, \quad \sigma > 1. \quad (2)$$

Credit Market Friction and Firm Behavior Firms face a working-capital (cash-in-advance) constraint. They must borrow from banks to pay wages before production takes place and revenues are obtained. This timing friction between costs and revenues is particularly relevant in developing countries where firms have limited internal liquidity and it is standard in emerging market business cycle models (e.g., Neumeyer and Perri, 2005; Jermann and Quadrini, 2012). This financial friction provides a direct transmission channel from financial markets (interest rates) to the real economy (labor demand).

In the baseline model, we assume that the wage bill must be paid in full before production takes place (we generalize this condition in the model extension). Firms borrow this amount from banks at gross interest rate R_l , which varies across locations. The total cost of production is therefore:

$$R_l w_l L_l. \quad (3)$$

Under perfect competition, firms price at marginal cost:

$$p_l = \frac{R_l w_l}{A_l}. \quad (4)$$

Combining the pricing equation with the demand system, labor demand in location l is:

$$L_l = A_l^{\sigma-1} w_l^{-\sigma} R_l^{-\sigma}. \quad (5)$$

Therefore, labor demand is increasing in productivity (given $\sigma > 1$) and decreasing in both wages and the cost of credit.

²As it is standard in this model, the assumption of $\sigma > 1$ ensures that labor demand is increasing in productivity and decreasing in cost.

Credit Supply from Banks Lending is intermediated by banks that operate branch networks in multiple locations. Each bank $b \in \mathcal{B}$ has total funds K_b to allocate across the locations where it operates. We model the allocation of bank lending following an Eaton-Kortum logic of selection and reallocation, similar to Kleinman et al. (2023). For each lending opportunity in location l , bank b draws an idiosyncratic efficiency φ_{bl} , reflecting branch-specific information, screening capacity and local borrower quality. These draws are independent across banks and regions and follow a Fréchet distribution, with cumulative distribution

$$F_b(\varphi) = \exp \left[- \left(\frac{\varphi}{\eta_b} \right)^{-\theta_B} \right] \quad (6)$$

and $\theta_B > 0$.

Bank b allocates its available funds to maximize expected returns. The return of bank b from lending in location l to a loan demand with idiosyncratic efficiency φ_{bl} is proportional to $\varphi_{bl}R_l/\kappa_{bl}$, where κ_{bl} captures location-specific operational costs. Each bank observes its vector of draws $\{\varphi_{bl}\}$ across potential projects in each location—for simplicity, we assume all potential projects demand one unit of capital—and chooses to allocate funds to all projects with highest returns. Therefore, the share of bank b 's funds allocated to location l is:

$$s_{lb} = \frac{(\eta_b R_l / \kappa_{bl})^{\theta_B}}{\sum_m (\eta_b R_m / \kappa_{bm})^{\theta_B}}. \quad (7)$$

This structure ensures that more attractive regions—those offering higher net returns or lower costs—receive a disproportionate share of total bank funding, while expected profitability is equalized across regions.³

Let K_b denote the total amount of funds available to bank b . Therefore, total credit supply in location l is:

$$B_l = \sum_{b \in \mathcal{B}} s_{lb} K_b. \quad (8)$$

Market Clearing Conditions and Equilibrium The loan market clears when credit supply equals credit demand in each location

$$B_l = w_l L_l. \quad (9)$$

Labor market clears when labor demand equals labor supply,

$$L_l = \bar{L}_l. \quad (10)$$

³The expected return is $v_{bl} = v_b = \gamma \left(\sum_{l \in \mathcal{L}_b} \left(\frac{\eta_b R_l}{\kappa_{bl}} \right)^{\theta_b} \right)^{1/\theta_B}$, see, e.g., Kleinman et al. (2023).

The market clearing conditions (9) and (10) combined with the expressions for total credit supply (8), labor demand (5) and firm prices (4) pin down the equilibrium wage and gross interest rate in each location.

II.B.1 Equilibrium Response to Climate Shocks

We next characterize the equilibrium response of this economy to a climate shock. Since labor is fixed in this simplified model, we are interested in how bank lending and equilibrium prices react to a climate shock. We allow the climate shock to operate through two margins: (i) climate-induced productivity shocks and (ii) shocks on credit supply due to bank liquidity exposure to climate shocks.

We denote the row vector of climate shocks across locations by $\hat{\mathbf{C}}$. We assume that location specific productivity A_l is affected by the climate shock in an isoelastic way. Denoting the log-change in productivity in location l by \hat{A}_l , we assume that

$$\hat{\mathbf{A}} = \gamma \hat{\mathbf{C}} \quad (11)$$

where $\hat{\mathbf{A}}$ denotes a column vector of productivity changes across locations and γ is the elasticity of productivity to the climate shock.

Likewise, we assume that overall bank funds available for lending are also affected by the climate shock with an elasticity of β ,

$$\hat{\mathbf{B}} = \beta \hat{\mathbf{C}}. \quad (12)$$

The parameter β captures changes in total bank lending capacity induced by climate exposure.

Therefore, we have that loans from bank b in location l , K_{lb} , can react to the climate shock because either the share of loans allocated to location l by bank b change, \hat{s}_{lb} , or the total amount of loans made by the bank change, \hat{K}_b . Formally, denoting with hats log changes, we have that since, by definition, $K_{lb} = s_{lb}K_b$, then $\hat{K}_{lb} = \hat{s}_{lb} + \hat{K}_b$.

Next, we can compute the total change in the loans in location l , \hat{K}_l , using the market clearing equilibrium (9) and the expression of the equilibrium share allocations, (7), to obtain the following,

$$\hat{B}_l = \theta_B \hat{R}_l - \theta_B \sum_{b \in \mathcal{B}} \text{Loan Share in location } l_b \cdot \text{Bank Exposure}_b + \sum_{b \in \mathcal{B}} s_{lb} \hat{K}_b, \quad (13)$$

where we define

$$\text{Loan share in location } l_b = \frac{s_{lb}K_b}{\sum_{b' \in \mathcal{B}} s_{lb'}K_b'} \quad (14)$$

as the share of loans of bank b in location l , and

$$\text{Bank Exposure}_b = \sum_{l \in \mathcal{L}} s_{lb} \hat{R}_l \quad (15)$$

is the loan-share weighted change in the price of loans, Denoting the \mathcal{L} by \mathcal{B} matrix of bank shares by location $\mathbf{N} = [s_{lb}]$ and by \mathbf{S} the \mathcal{L} by \mathcal{B} matrix that has in entry lb the share of capital in location l coming from bank b as defined in equation (14),⁴ we obtain the following matrix representation for changes in loan supply

$$\hat{\mathbf{B}} = \theta_B (\mathbf{I} - \mathbf{S}\mathbf{N}') \hat{\mathbf{R}} + \beta \mathbf{S}\mathbf{N}' \hat{\mathbf{C}} \quad (16)$$

where \mathbf{I} denotes the identity matrix and \mathbf{N}' the transpose of \mathbf{N} . Loan demand comes from the cash-in-advance constraint, which implies that

$$\hat{\mathbf{B}} = \hat{\mathbf{w}} + \hat{\mathbf{L}} \quad (17)$$

Finally, labor demand also is affected by the climate shock, since location-specific productivity is directly affected and prices also adjust. Log-differentiating the labor demand Equation (5), we obtain

$$\hat{\mathbf{L}} = (\sigma - 1)\gamma \hat{\mathbf{C}} - \sigma \hat{\mathbf{w}} - \sigma \hat{\mathbf{R}}. \quad (18)$$

In this simplified environment, employment is fixed by assumption; bank shocks affect wages and borrowing costs. Employment responses arise once labor mobility is introduced in the next section.

Furthermore, since labor supply is fixed, we know that in equilibrium

$$\hat{\mathbf{L}} = 0,$$

implying that productivity changes are fully translated into prices,

$$\hat{\mathbf{w}} + \hat{\mathbf{R}} = \frac{(\sigma - 1)}{\sigma} \gamma \hat{\mathbf{C}} \quad (19)$$

We can combine the demand and supply equations in logarithmic deviation for bank loans and labor, to obtain an exact expression for changes in loans across locations⁵

$$\hat{\mathbf{B}} = \left(\frac{\sigma - 1}{\sigma} \gamma \right) \hat{\mathbf{C}} - [(1 + \theta_B)\mathbf{I} - \theta_B \mathbf{S}\mathbf{N}']^{-1} \left[\left(\frac{\sigma - 1}{\sigma} \gamma \right) \mathbf{I} - \beta \mathbf{S}\mathbf{N}' \right] \hat{\mathbf{C}}. \quad (20)$$

⁴We also use equation (12) combined with $\hat{K}_b = \sum_{l \in \mathcal{L}} s_{lb} \hat{K}_l b$. This result follows from the fact that $\sum_{l \in \mathcal{L}} s_{lb} = 1$, which implies that $\sum_{l \in \mathcal{L}} s_{lb} \hat{s}_{lb} = 0$.

⁵We also have that $\hat{\mathbf{B}} = \hat{\mathbf{w}}$, $\hat{\mathbf{R}} = [(1 + \theta_B)\mathbf{I} - \theta_B \mathbf{S}\mathbf{N}']^{-1} [(\frac{\sigma-1}{\sigma}\gamma) \mathbf{I} - \beta \mathbf{S}\mathbf{N}'] \hat{\mathbf{C}}$ and $\hat{\mathbf{p}} = -\frac{\gamma}{\sigma} \hat{\mathbf{C}}$.

Approximate Solution Next, we provide a first-order approximation of the exact solution for changes in loans, Equation (20). The bank location network enters the equilibrium conditions through the matrix \mathbf{SN}' , which aggregates lending exposures across banks and locations using probability weights. Because each bank allocates lending across many locations, individual lending shares are small, and consequently the entries of \mathbf{SN}' are typical of small magnitude (of the order $1/\mathcal{L}$). In this environment, applying \mathbf{SN}' once to $\hat{\mathbf{C}}$ corresponds to a first-round averaging of shocks across network-connected locations, while higher-order powers such as $(\mathbf{SN}')^2$ represent repeated rounds of averaging and are quantitatively small. We therefore approximate equilibrium objects to the first order in the network matrix \mathbf{SN}' , retaining only linear terms and neglecting terms of order $(\mathbf{SN}')^2$ and higher. This first-order approximation captures the dominant propagation of shocks through shared bank exposures while remaining tractable and transparent.⁶

We find that the first-order approximation to the change in bank loans is

$$\hat{\mathbf{B}} \approx \underbrace{\frac{\theta_B}{1 + \theta_B} \left(\frac{\sigma-1}{\sigma} \gamma \right) \hat{\mathbf{C}}}_{\text{Direct Effect}} + \underbrace{\left(\frac{\beta}{1 + \theta_B} - \frac{\theta_B}{(1 + \theta_B)^2} \left(\frac{\sigma-1}{\sigma} \gamma \right) \right) \mathbf{SN}' \hat{\mathbf{C}}}_{\text{Indirect Effect}}. \quad (21)$$

This equation provides a good intuition of the forces in the model. The first term in Equation (21) captures the direct effect that a climate shock in location l has on loans in location l . This is mediated through the effect on productivity in location l which affects the efficiency of production, and therefore the price firms can charge, its sales and its labor demand. Due to financial frictions, this translates into loan demand.

The second term captures indirect effects through the bank network. To grasp a better intuition, note that the l th entry in the indirect effect vector is

$$[\mathbf{SN}' \hat{\mathbf{C}}]_l = \sum_{b \in \mathcal{B}} \text{Loan Share in location } l_b \cdot \text{Bank Exposure to Climate Shock } b,$$

where we define the Loan Share in location l_b as in Equation (14) and

$$\text{Bank Exposure to Climate Shock} = \sum_{l \in \mathcal{L}} s_{lb} \hat{C}_l. \quad (22)$$

Therefore, the vector $\mathbf{SN}' \hat{\mathbf{C}}$ captures exposure to climate shocks in the set of locations that share lenders with l . Mathematically, it takes the form of an average climate shock across the locations that receive funds from the banks that finance location l . The coefficient on $\mathbf{SN}' \hat{\mathbf{C}}$ aggregates two effects: a supply component (banks' funds move with climate exposure, governed by β) and a reallocation component (banks tilt lending toward

⁶Formally, equilibrium expressions involve the inverse of matrices of the form $(\mathbf{I} - \rho \mathbf{SN}')$, with $\rho \in (0, 1)$. When $\rho \mathbf{SN}'$ is a contraction as in our case, this inverse admits a Neumann series representation $(\mathbf{I} - \rho \mathbf{SN}')^{-1} = \sum_{k=0}^{\infty} (\rho \mathbf{SN}')^k$. Our approximation truncates this expansion at first order, $(\mathbf{I} - \rho \mathbf{SN}')^{-1} \approx \mathbf{I} + \rho \mathbf{SN}'$, dropping higher-order terms that correspond to multiple rounds of network propagation.

locations with higher returns, governed by θ_B).

The interpretation of the first effect, $\beta/(1 + \theta_B)$ is that of a supply shock: when bank b 's total funds fall when its portfolio is exposed to climate shocks, then locations funded by that bank see reduced credit supply. The weighting is exactly through how much l relies on bank b (share of lending in l coming from b) and which locations load into bank b 's exposure (s_{lb}).

The interpretation of the second effect $\frac{\theta_B}{1+\theta_B} \left(\frac{\sigma-1}{\sigma} \gamma \right)$ is one of banks shift lending toward locations with relatively higher loan returns. Intuitively, neighbors' credit demand and profitability move loan supply around through shared bank networks. Neighbors here are not geographic; they are network neighbors in bank space. When climate shocks change fundamentals in some locations (here productivity, via $\gamma \hat{\mathbf{C}}$), those locations' equilibrium loan rates and wages adjust. Banks then reallocate, and a location's borrowing depends on neighbors' conditions because bank portfolios tie them together. Mathematically, that shows up as \mathbf{SN}' multiplying $\hat{\mathbf{R}}$ in the loan supply equation, and after solving, it becomes a term proportional to $\mathbf{SN}' \hat{\mathbf{C}}$ even if $\beta = 0$. Finally note that these two effects have opposite signs, which one dominates is an empirical question.

II.C EXTENSION: LABOR MOBILITY AND PARTIAL FINANCIAL FRICTIONS

The simplified framework studied above isolates the core mechanism of the model—capital reallocation across locations through bank networks in response to climate shocks—by abstracting from labor mobility and assuming that all production costs are subject to a cash-in-advance constraint. In this environment, we have shown that equilibrium adjustments operate entirely through credit prices and bank lending, making transparent how shocks propagate across locations via shared financial intermediaries. We now extend the model along two dimensions. First, we allow workers to relocate across locations in response to wage differentials, introducing an endogenous labor supply margin. Second, we relax the cash-in-advance assumption by allowing only a fraction of production costs to require external financing. These extensions preserve the central credit reallocation mechanism highlighted above while enriching the model's adjustment channels and bringing it closer to the features observed in the data.

Partial Cash-in-Advance Constraint We relax the full cash-in-advance assumption by allowing only a fraction of production costs to require external financing. Specifically, we assume that a share $\tilde{k} \in (0, 1]$ of the wage bill must be paid in advance using bank loans, while the remaining share $1 - \tilde{k}$ can be financed internally.

This modification reduces firms' exposure to credit market conditions and weakens the direct link between wages, employment, and borrowing. As a result, loan demand in each location becomes proportional to $\tilde{k} w_l L_l$, and changes in credit prices affect production costs and labor demand only through this financed share. In equilibrium, the

cash-in-advance constraint continues to tie borrowing to local economic activity, but the strength of this channel is now governed by \tilde{k} . When $\tilde{k} = 1$, the model nests the full cash-in-advance benchmark; as \tilde{k} decreases, the economy becomes less sensitive to credit shocks, attenuating both the direct effect of changes in loan rates on production costs and the indirect propagation of shocks through bank lending networks. This implies that production costs are now $[(1 - \tilde{k}) + \tilde{k}R_l] w_l L_l \equiv \tilde{k}\tilde{R}_l w_l L_l$, and consequently the equilibrium price becomes $p_l = \tilde{k}\tilde{R}_l w_l / A_l$.

Labor Supply and Migration Workers are initially distributed across locations with L_o^0 workers born in origin o . Workers choose where to live based on real wages and idiosyncratic preference shocks. The indirect utility of a worker i born in o who moves to l is:

$$V_{i,o \rightarrow l} = \ln w_l - \ln \tau_{ol} + \frac{1}{\theta} \epsilon_{il}, \quad (23)$$

where τ_{ol} captures bilateral migration costs and ϵ_{il} is an i.i.d. Gumbel taste shock. The parameter θ governs the dispersion of preferences: larger values imply that wage differentials matter more for location choices.

The share of workers from origin o choosing destination l is:

$$\pi_{ol} = \frac{(w_l / \tau_{ol})^\theta}{\sum_d (w_d / \tau_{od})^\theta}. \quad (24)$$

Total labor supply in location l is:

$$L_l = \sum_o \pi_{ol} L_o^0. \quad (25)$$

Generalized Working-Capital Requirement While labor is the only production input in the model, in practice firms also rely on short-term credit to finance non-wage working-capital expenditures, such as inventories, energy, logistics, and other operating costs. Many of these costs are incurred up front and scale with employment adjustments rather than with the steady-state wage bill. We capture this by assuming that, in addition to financing payroll, a marginal expansion of employment requires extra working capital equal to a fraction $\psi \geq 0$ of the financed payroll per additional worker. As a result, changes in borrowing respond more than proportionally to changes in employment. We assume that this working capital is sourced from outside the local labor market (e.g. imported or provided by national financial intermediaries) at an exogenous price, implying that employment expansions raise financing needs but do not directly increase local labor demand beyond payroll itself. Log-linearizing around an initial equilibrium without net employment adjustment yields

⁶Formally, we assume that a small change in employment requires additional working capital proportional to the loan-financed payroll, so that $dB_l = \tilde{k}d(w_l L_l) + \psi k w_l dL_l$. Using $d(w_l L_l) = L_l dw_l + w_l dL_l$

$$\hat{\mathbf{B}} = \hat{\mathbf{w}} + (1 + \psi)\hat{\mathbf{L}}. \quad (26)$$

This formulation implies that labor reallocation effects are mechanically amplified in loan outcomes relative to employment, an implication that plays an important role in the propagation of shocks through the banking network.

II.C.1 Equilibrium Response to Climate Shocks in the Extended Model

The model yields four equilibrium conditions. First, labor supply responds to wage changes according to:

$$\hat{\mathbf{L}} = \theta \underbrace{(\mathbf{I} - \mathbf{\Gamma}'\mathbf{\Pi})}_{\equiv \mathbf{A}_L} \hat{\mathbf{w}}, \quad (27)$$

where $\mathbf{\Gamma} = [\gamma_{ol}]$ with $\gamma_{ol} = f_{ol}/L_l$ being the share of workers in l coming from o , and $\mathbf{\Pi} = [\pi_{ol}]$ is the matrix of migration shares. The matrix \mathbf{A}_L captures how labor supply responds to wage changes, accounting for migration networks. Labor supply is analogous to Borusyak et al. (2023), among others and we thus relegate its analysis to the appendix.

The labor demand expression remains analogous to our benchmark model, but with the cost of capital being now $(1 - \tilde{k}) + \tilde{k}R_l$. We proceed by assuming that $R_l - 1$ is close to zero, so that $R_l - 1 \simeq \hat{R}_l$. This implies that labor demand is, to first-order approximation,

$$\hat{\mathbf{L}} = (\sigma - 1)\gamma \hat{\mathbf{C}} - \sigma \hat{\mathbf{w}} - \sigma \tilde{k} \hat{\mathbf{R}}. \quad (28)$$

This expression is intuitive: changes in labor demand are as in our benchmark model attenuating the effect of the gross interest rate by $\tilde{k} \leq 1$.

Finally, since \tilde{k} is a constant, changes in loan supply remain the same as in our benchmark model, Equation (16), while loan demand is augmented to allow for working capital, (26). Combining these two equations with the new labor demand and supply equations, we obtain an exact solution of the system of equations in the appendix. More interestingly, we can then provide a first-order approximation of the exact solution. We combine our diffuse network argument above for \mathbf{SN}' with the low-mobility approximation discussed in Borusyak et al. (2023) for the labor response to wage changes \mathbf{A}_L . In a nutshell, the low mobility assumption implies that a small fraction of the population in any given location move to other locations.⁷

and dividing by the steady-state loan-financed wage bill $\tilde{k}w_l L_l$ yields $\frac{dB_l}{\tilde{k}w_l L_l} = \frac{dw_l}{w_l} + (1 + \psi)\frac{dL_l}{L_l}$. Since adjustment-related borrowing is zero in steady state, baseline borrowing equals the financed wage bill, and replacing B_l by $\tilde{k}w_l L_l$ in the denominator introduces only second-order errors. This yields the result in Equation (26).

⁷More concretely, Borusyak et al. (2023) show that \mathbf{A}_L can be approximated by a sparse operator $-\mathbf{D}(\mathbf{I} - \mathbf{W})$ where \mathbf{D} scales with local mobility intensity and \mathbf{W} captures small cross-location spillovers; keeping only first-order terms in $\mathbf{D}(\mathbf{I} - \mathbf{W})$ yields a transparent decomposition into direct and indirect labor adjustment. In particular they argue that $\mathbf{I} - \mathbf{\Gamma}'\mathbf{\Pi} = -(\Delta\mathbf{\Gamma} + \Delta\mathbf{\Pi})$ whose l th entry is

To express the results of the first-order approximation, we introduce the following notation:

$$\chi = \frac{(\sigma - 1)\gamma\theta_B}{\sigma(\theta_B + \tilde{k})}, \quad \xi = \frac{\tilde{k}}{\theta_B + \tilde{k}}\beta - \frac{\tilde{k}\theta_B}{(\theta_B + \tilde{k})^2} \frac{\sigma - 1}{\sigma} \gamma. \quad (29)$$

$$\xi = \frac{\tilde{k}}{\theta_B + \tilde{k}}(\beta - \chi) \quad (30)$$

We denote by \mathbf{F}/\mathbf{M} the $\mathcal{L} \times \mathcal{L}$ matrix whose kl th entry corresponds to the share of bilateral migration flows between locations k and l out of total migration from l , F_{kl}/M_l for $k \neq l$ and is zero otherwise (i.e., on the diagonal). Our baseline results proceed with the additional assumption that the share of migrants, $M_l/L_l \simeq \bar{m}$, is approximately constant across locations. This assumption implies that heterogeneity in labor spillovers comes from the network structure \mathbf{F}/\mathbf{M} , not from differences in migration intensity across locations.⁸

The first-order approximation of the equilibrium response of bank loans is analogous to our baseline model augmented by an additional term capturing labor mobility. The equilibrium response of **credit** is

$$\hat{\mathbf{B}} \approx \chi \left(1 + 2(1 + \psi)\theta \bar{m}\right) \hat{\mathbf{C}} - 2(1 + \psi)\theta \chi \bar{m} \frac{\mathbf{F}}{\mathbf{M}} \hat{\mathbf{C}} + \xi \left(1 + 2(1 + \psi)\theta \bar{m}\right) \mathbf{SN}' \hat{\mathbf{C}}. \quad (31)$$

The equilibrium response of **employment** is

$$\hat{\mathbf{L}} \approx 2\theta \chi \bar{m} \hat{\mathbf{C}} - 2\theta \chi \bar{m} \frac{\mathbf{F}}{\mathbf{M}} \hat{\mathbf{C}} + 2\theta \xi \bar{m} \mathbf{SN}' \hat{\mathbf{C}}. \quad (32)$$

We refer to the coefficient on $\hat{\mathbf{C}}$ as the direct effect, the coefficient on $\frac{\mathbf{F}}{\mathbf{M}} \hat{\mathbf{C}}$ as the labor-network effect, and on $\mathbf{SN}' \hat{\mathbf{C}}$ as the bank-network effect. They play a central role in our empirical analysis and we discuss them next in turn.

II.C.2 Interpretation and mapping to empirical specification

These expressions show that both employment and credit responses depend on:

Direct effect. This is the first element in equations (31) and (32), and captures how a local productivity shock driven by climate (\hat{C}_l) affects local credit and employment. A

$$[(\Delta\mathbf{\Pi} + \Delta\mathbf{\Gamma}') \hat{\mathbf{D}}]_l = -2 \frac{M_l}{L_l} \left(\underbrace{\hat{D}_l}_{\text{Labor Direct}} - \underbrace{\sum_{k \neq l} \frac{F_{kl}}{M_l} \hat{D}_k}_{\text{Labor Indirect}} \right). \text{ Furthermore, because both } \mathbf{W} \text{ and } \mathbf{SN}' \text{ have}$$

entries of order $1/\mathcal{L}$, their product is second order and negligible in a first-order approximation, see Appendix C.B.

⁸We derive in Appendix C.B the first-order approximation without this assumption, which we also test in the data, and find that it does not make a significant quantitative difference relative to our baseline.

negative climate shock reduces agricultural productivity, lowering credit and labor demand directly.

Indirect effect via migration network. This is the second element in equations (31) and (32). It captures spillovers through migration. When connected regions experience negative shocks, workers migrate toward location l , increasing local labor supply. The strength of this channel depends on the pre-existing migration network.

The term $\frac{\mathbf{F}}{\mathbf{M}}\hat{\mathbf{C}}$ is a matrix-vector product where \mathbf{F} is the matrix of bilateral migration flows. For location ℓ :

$$\left(\frac{\mathbf{F}}{\mathbf{M}}\hat{\mathbf{C}}\right)_\ell = \sum_{k \in \mathcal{L}} \frac{F_{k\ell}}{M_\ell} \hat{C}_k \quad (33)$$

where $F_{k\ell}$ denotes the flow of migrants from location k to location ℓ , and $M_\ell = \sum_k F_{k\ell}$ is the total number of migrants in ℓ . This is a weighted average of climate shocks in origin regions, where the weights are the shares of migrants coming from each origin.

Indirect effects via capital markets. This is the third element in equations 31 and 32. It captures spillovers through bank branch networks (matrix \mathbf{SN}'). When regions served by the same banks experience negative shocks, banks may reallocate lending or face liquidity constraints, affecting credit supply in location l .

The term $\mathbf{SN}'\hat{\mathbf{C}}$ captures exposure through the bank branch network. For location ℓ :

$$\left(\mathbf{SN}'\hat{\mathbf{C}}\right)_\ell = \sum_{k \in \mathcal{L}} (\mathbf{SN})_{\ell k} \hat{C}_k \quad (34)$$

where $(\mathbf{SN})_{\ell k} = \sum_b \omega_{\ell b} s_{kb}$ measures how connected location ℓ is to location k through shared banks. Here $\omega_{\ell b}$ is the share of credit in ℓ from bank b , and s_{kb} is the share of bank b 's lending going to location k .

A key insight from the model is that failing to account for indirect effects leads to biased estimates of the direct effect. When shocks are spatially correlated—as is the case with climate change—regions connected through labor and capital networks experience correlated shocks, creating omitted variable bias if these connections are ignored.

Coefficient Signs: Labor Mobility The model delivers sharp sign predictions for employment responses to climate shocks. Because dryness reduces local productivity ($\gamma < 0$), the direct effect of a local climate shock on employment is negative: higher dryness lowers labor demand and reduces employment in the affected location. At the same time, the indirect labor effect, captured by exposure to climate shocks in connected locations through migration flows, necessarily enters with the opposite sign. Intuitively, when other locations experience adverse shocks, relative labor demand shifts toward less-affected areas, inducing inflows of workers. As a result, the coefficients on direct exposure and

labor-network exposure are of opposite sign by construction.

This sign reversal is a robust implication of the spatial labor-supply structure and does not depend on the details of the credit market. It reflects the fact that labor mobility responds to relative economic conditions across locations: local adverse shocks push workers out, while adverse shocks elsewhere pull workers in. Importantly, this prediction provides a clean empirical diagnostic for the labor reallocation mechanism emphasized in the model.⁹

Coefficient Signs: Loans In contrast to employment, the sign of the loan response to bank-network exposure is theoretically ambiguous because they respond to both supply and demand forces. Dryness propagates through banks via two opposing channels. First, a credit supply channel operates through $\beta < 0$: adverse shocks to bank-exposed locations reduce the overall availability of funds, lowering lending elsewhere. Second, a demand reallocation channel arises because shocks change the relative profitability and scale of production across locations, inducing shifts in desired borrowing.

Which force dominates is an empirical question. If balance-sheet contractions are severe, loan volumes decline in bank-exposed locations. If instead demand reallocation effects are strong, lending may increase in less-affected areas despite aggregate credit tightening. The model therefore predicts that loan responses to bank-network exposure need not mirror employment responses and may differ in sign, a feature that aligns naturally with observed heterogeneity in credit-market outcomes.

Magnitudes of Coefficients A central magnitude implication of the model is that labor responses are quantitatively smaller than loan responses. All labor adjustments operating through migration are scaled by the ratio M_l/L_l , where M_l denotes gross migration flows and L_l the local workforce. Because migration rates are small at annual frequencies, this ratio is well below one, mechanically dampening both direct and indirect labor responses. In contrast, loan responses include components that are not scaled by migration intensity, allowing bank-network effects to be substantially larger for borrowing than for employment.

Moreover, when working-capital requirements extend beyond wages, as captured by the parameter $\psi > 0$, labor reallocation effects are amplified in loan volumes relative to employment. A given change in employment then translates into a more-than-proportional change in borrowing, further widening the gap between the magnitudes of loan and labor responses.

⁹The effect of climate shocks transmitted through the banking network on employment is typically negative. Dryness reduces bank balance sheets and loan supply ($\beta < 0$), which raises borrowing costs in bank-exposed locations and depresses labor demand. Although there is also a general-equilibrium reallocation component—whereby reduced demand in affected locations may free up credit elsewhere—the supply contraction dominates under empirically relevant parameter values. Consequently, exposure to bank-connected locations experiencing dryness leads to lower employment.

Role of \tilde{k} , θ , and σ The strength of the credit channel is governed by three key parameters. First, \tilde{k} , the fraction of production costs requiring external finance, scales the sensitivity of labor demand and wages to loan-rate movements. When \tilde{k} is small, borrowing costs matter little for production decisions, attenuating bank-network effects on employment. As \tilde{k} rises, credit-market disruptions increasingly transmit to real activity.

Second, θ_B , the dispersion parameter governing bank lending allocation, determines how elastically credit is reallocated across locations in response to changes in loan rates. A higher θ_B , reduces the variance of idiosyncratic draws from Equation (6) and therefore strengthens network propagation by making banks more responsive to relative returns across regions. Finally, the elasticity of substitution σ controls the responsiveness of product demand to cost changes. Higher σ amplifies the impact of both productivity and credit shocks on labor demand, reinforcing all channels of adjustment.

Connection with the Empirical Design The first-order approximations map directly to estimating equations with three types of regressors: direct climate shocks, indirect exposure via migrants, and indirect exposure via banks. Both the employment and the credit approximation for a given location l can be written into three separate terms:

$$\hat{L}_\ell \approx \underbrace{\beta_1^L \cdot \hat{C}_\ell}_{\text{Direct effect}} + \underbrace{\beta_2^L \cdot \sum_{k \neq \ell} \frac{F_{k\ell}}{M_\ell} \hat{C}_k}_{\text{Indirect Eff. via migrants}} + \underbrace{\beta_3^L \cdot \sum_{k \neq \ell} (SN)_{\ell k} \hat{C}_k}_{\text{Indirect Effect via banks}} \quad (35)$$

where the structural coefficients are:

$$\beta_1^L = 2\theta \bar{m} \chi = 2\theta \bar{m} \frac{(\sigma - 1)\gamma \theta_B}{\sigma(\theta_B + \tilde{k})} \quad (\text{Direct effect})$$

$$\beta_2^L = -2\theta \bar{m} \chi = -2\theta \bar{m} \frac{(\sigma - 1)\gamma \theta_B}{\sigma(\theta_B + \tilde{k})} \quad (\text{Indirect via migrants})$$

$$\beta_3^L = 2\theta \bar{m} \xi = 2\theta \bar{m} \left[\frac{\tilde{k}}{\theta_B + \tilde{k}} \beta - \frac{\tilde{k} \theta_B}{(\theta_B + \tilde{k})^2} \frac{\sigma - 1}{\sigma} \gamma \right] \quad (\text{Indirect via banks})$$

Similarly, the credit approximation for location ℓ :

$$\hat{B}_\ell \approx \underbrace{\beta_1^B \cdot \hat{C}_\ell}_{\text{Direct effect}} + \underbrace{\beta_2^B \cdot \sum_{k \neq \ell} \frac{F_{k\ell}}{M_\ell} \hat{C}_k}_{\text{Indirect Eff. via migrants}} + \underbrace{\beta_3^B \cdot \sum_{k \neq \ell} (SN)_{\ell k} \hat{C}_k}_{\text{Indirect Eff. via banks}} \quad (36)$$

where the structural coefficients are:

$$\begin{aligned}\beta_1^B &= \frac{(\sigma - 1)\gamma \theta_B}{\sigma(\theta_B + \tilde{k})} \left(1 + 2(1 + \psi)\theta \bar{m}\right) && \text{(Direct effect)} \\ \beta_2^B &= -2(1 + \psi)\theta \bar{m} \frac{(\sigma - 1)\gamma \theta_B}{\sigma(\theta_B + \tilde{k})} && \text{(Indirect via migrants)} \\ \beta_3^B &= \left[\frac{\tilde{k}}{\theta_B + \tilde{k}} \beta - \frac{\tilde{k} \theta_B}{(\theta_B + \tilde{k})^2} \frac{\sigma - 1}{\sigma} \gamma \right] \left(1 + 2(1 + \psi)\theta \bar{m}\right) && \text{(Indirect via banks)}.\end{aligned}$$

In sum, the first-order approximation of our theory delivers a direct mapping between empirical coefficients in regressions of $\hat{\mathbf{L}}$ and $\hat{\mathbf{B}}$ on the three exposure measures and the underlying structural parameters $(\sigma, \theta, \theta_B, \tilde{k}, \psi, \beta, \gamma)$.

III EMPIRICAL STRATEGY

The model in Section II predicts that regional productivity shocks induced by climate change propagate across space through labor migration networks and bank branch networks, generating both direct effects in affected regions and indirect effects in connected regions. To bring these predictions to data, we exploit variation in productivity shocks induced by drought conditions across Brazilian municipalities over the past two decades.

We identify productivity shocks induced by climate change using changes in meteorological dryness relative to historical averages in each region (Section III.A). We then present an estimating equation that map directly to the model's predictions and identifies: i) direct responses to persistent changes in climate and ii) indirect responses to exposure to excess dryness via capital and labor market connections (Section III.B).

III.A VARIATION IN METEOROLOGICAL DRYNESS ACROSS BRAZILIAN REGIONS

Brazil's climate has started experiencing several of the predicted effects of global warming, including higher temperatures and lower precipitations. Figure Ia shows that the average temperature in Brazil has been steadily increasing since 1920, from 22.5 to 24°C.¹⁰ Climate models predict that global warming increases precipitation in high and low latitudes but decreases it in middle ones, which encompass the majority of Brazilian regions (IPCC 2021, page 645). The combination of higher temperature and lower precipitation is expected to lead to an increase in the frequency and duration of droughts in Brazil. This trend has been already documented in the climatology literature (Cunha et al. 2019) and is visible in the time series of natural disasters reported by the National System of

¹⁰This 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. For a detailed discussion, see section 1.4.2 on page 193, Figure TS.23 on page 133 and FAQ 1.3 on page 246 of IPCC (2021).

Civil Protection or SINPDEC (Sistema Nacional de Proteção e Defesa Civil) reported in Figure Ib.¹¹

Figure C1 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. We rely on a meteorological measure of dryness, the Standardized Precipitation and Evapotranspiration Index, or SPEI (Vicente-Serrano et al. 2010). The index compares the amount of precipitation in a given area with its potential evapotranspiration needs, which are a function of local temperature.¹² Crucially for our purposes, SPEI measures standard *deviations* of dryness relative to the historical average observed in a given locality.¹³ Thus, SPEI has been used by the climatological literature to predict droughts caused by climate change (Dubrovsky et al. 2009; Vicente-Serrano et al. 2010). Indeed, we show in Online Appendix A 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 II, we report the geographical distribution of average $\Delta Dryness$ in the 2001-2010 decade and the 2011-2018 decade. Consistently with the increase in the frequency of reported droughts described above, excess dryness has increased over the past two decades and displays large variation across regions. We exploit this regional heterogeneity to construct a differences-in-differences empirical strategy to identify the potential effects of climate change on local factor markets.

¹¹The 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. 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.

¹²Potential evapotranspiration is defined as the evaporation from an extended surface of a short green crop which fully shades the ground, exerts little or negligible resistance to the flow of water, and is always well supplied with water. Note that this land use is assumed when computing the index regardless of actual land use. SPEI captures the climatic water balance in a given location, with positive values indicating a water surplus (precipitation larger than PET) and negative values indicating a water deficit (precipitation smaller than PET).

¹³SPEI is a standardized index, i.e. SPEI equal to -1 in year t implies that the difference between observed rain and potential evapotranspiration needs in year t are one standard deviation lower than the average observed in the baseline period in a given locality.

Importantly, changes in average dryness in the first decade of the 2000s relative to historical averages display a weaker correlation with initial characteristics of municipalities compared to reported droughts. Table I shows that the correlation between excess dryness during the 2001-2010 period and baseline municipality characteristics is substantially lower than the correlation between reported droughts and the same characteristics. Furthermore, our main results show that estimates remain stable when including these controls.

Finally, Figure III reports the distribution of $\Delta Dryness$ across Brazilian municipalities in the first and second decade of the 2000s. As shown, while the distribution of dryness in the first decade is centered around its average observed in the previous century, dryness appears to be drawn from a warmer distribution in the second decade. This is consistent with the trend reported in Figure Ib, which shows an increase in the frequency of droughts across Brazilian regions during the last ten years relative to the previous decade. Figure III also reports the median (black line) and 90th percentile (red line) of the distributions of excess dryness across municipalities in each decade. All quantifications in the paper are computed for a municipality moving from the median to the 90th percentile of excess dryness, which corresponds to about 1 standard deviation in the 2000-2010 decade, and to 1.36 standard deviations in the 2011-2018 decade.

III.B ESTIMATING EQUATION AND MAPPING TO THE MODEL

The model shows that the equilibrium response of employment and credit to climate shocks can be decomposed into three components: (i) the direct local effect of the productivity shock; (ii) indirect effects via capital markets, captured by the bank network matrix SN ; and (iii) indirect effects via labor markets, captured by the migration network matrix F/M . We test these predictions by estimating the following differences-in-differences specification:

$$\begin{aligned}
 \Delta y_{\ell} = & \alpha_r + \underbrace{\beta_1 \Delta Dryness_{\ell}}_{\text{Direct effect}} \\
 & + \underbrace{\beta_2 Exposure_{\ell}^K}_{\text{indirect effects via branch network}} + \underbrace{\beta_3 Exposure_{\ell}^L}_{\text{indirect effects via migrant network}} \\
 & + \Lambda X_{\ell} + \varepsilon_{\ell}
 \end{aligned} \tag{37}$$

Where ℓ indexes municipalities and r indexes one of the five macro-region of Brazil (North, Northeast, Central-West, South and Southeast).¹⁴ Macro-region fixed effects (α_r) cap-

¹⁴Since borders of municipalities changed over time, 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.

ture any common shock at the macro-region level, and $X_{\ell,t=1991}$ control for different trends across municipalities with different baseline characteristics, including share of rural population, income per capita, literacy rates and population density.

The outcome variables capture changes in credit and labor outcomes between 2000 and 2010 (in logs). We focus on these two years because of the timing of the Brazilian Population Census. We now describe the construction of the key explanatory variables and their mapping to the model.

Direct effects. $\Delta Dryness_{l,2001-2010}$ captures the average level of dryness experienced by municipality l over the years 2001 to 2010 relative to the level of dryness historically recorded in the same municipality between 1901 and 1999. The construction of this measure is described in detail in section III.A. It is the empirical counterpart of the climate shock \hat{C} in the model.

Indirect effects via bank branch network. The model shows that changes in credit in location l depend on shocks experienced by other locations served by the same banks. We construct the empirical counterpart of the measure of exposure via the bank branch network $\mathbf{SN}'\hat{C}$ in two steps.¹⁵

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:

$$\text{Bank Exposure}_b = \sum_{l' \in \text{Network}_b} s_{l'b} \Delta Dryness_{l',2001-2010} \quad (38)$$

where the weights $s_{l'b}$ are the share of total loans of bank b originated in municipality l' in the baseline year 2000, and O_b is the set of municipalities in which bank b was present in 2000. This weighting corresponds to the \mathbf{N} matrix in the model: it captures how shocks in different locations affect each bank's funding base.

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

$$Exposure_l^K = \sum_{b \in B_l} \omega_{lb} \text{Bank Exposure}_b \quad (39)$$

where the weights ω_{lb} capture the lending market share of bank b in municipality l , constructed as the value of outstanding loans originated by branches of bank b in municipality l divided by the total value of loans issued by branches of all banks operating in municipality l (whose set we indicate with B_l) in the baseline year 2000. This weighting corresponds to the \mathbf{S} matrix in the model: it captures how each bank's exposure translates into changes in credit in each municipality it serves.

¹⁵This methodology is similar to the approach proposed in Bustos et al. (2020).

Indirect effects via migrant networks. The model shows that labor supply in location l depends on shocks experienced by locations connected through migration networks. This mechanism is captured by network structure $\frac{\mathbf{F}}{\mathbf{M}}$. When origin regions experience negative productivity shocks, workers migrate toward destinations with pre-existing migrant networks, increasing labor supply there. We construct an empirical counterpart to $\frac{\mathbf{F}}{\mathbf{M}}$ using data from past migration flows. The classic justification for this measure is that migrants tend to choose destinations that were previously chosen by migrants from their same origin region because social networks reduce migration costs (Altonji and Card 1991; Card 2001). For example, former migrants from the same origin might offer labor market referrals that reduce job search costs.

The Brazilian Census allows us to construct internal migration flows based on a question asking respondents for their municipality of residence five years prior to the Census year. Using the 2000 Census, we can calculate 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:

$$Exposure_l^L = \sum_{l' \neq l} \alpha_{l,l'} \Delta Dryness_{l',2001-2010}, \quad (40)$$

with

$$\alpha_{l,l'} = \frac{M_{1995-2000,l' \rightarrow l}}{M_{l,2000}},$$

where $M_{1995-2000,l' \rightarrow l}$ is the number of migrants that moved from l' to l in the period 1995 to 2000 (i.e. individuals observed in l in 2000 that declared to be living in l' in 1995), and $M_{l,2000}$ is the total number of migrants in l as of 2000.

The weight $\alpha_{l,l'}$ captures the degree of connection via past migrants between two municipalities. Thus, $Exposure_l^L$ is the empirical counterpart of how productivity shocks propagate through the migration network in the model.

III.B.1 Discussion of identification assumptions

Equation (37) is similar to the long-differences approach described in Burke and Emerick (2016), in which long-run changes in outcomes are regressed on long-run changes in temperatures. Consistent estimation of equation (37) requires identifying assumptions on both the direct effect of local climate shocks and the indirect effects operating through bank and migration networks. We discuss these assumptions in turn.

Identification of direct effects. The key identifying assumption for the direct effect 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. 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, Panel B of Table I shows that there is no correlation between excess dryness during the 2001-2010 period and a set of baseline municipality characteristics reflecting the level of development.

A second concern is reverse causality: changes in local economic activity might affect local climate. For example, there is evidence in natural sciences that changes in land use—such as the conversion of forest to pasture or cultivated agricultural land—can affect local climate (Spracklen et al. 2018; Lawrence and Vandecar 2015). This concern is particularly relevant for Brazil, which experienced a vast increase in cropland in the first decade of the 2000s, often at the expense of pasture land and forest. This, in turn, might have contributed to lower rainfall and higher dryness (Araujo 2023). However, excess dryness is uncorrelated with deforestation of the Amazon rain forest during the period under study (Panel B of Table I). In addition, in the empirical analysis, we control for measures of technical change in soy and maize—the main crops farmed in Brazil and those that experienced significant technological improvements during the period under study. Soy and maize technical change are defined as the theoretical increases in potential yields of these two crops obtained by switching from traditional to advanced agricultural techniques as described in Bustos et al. (2016).

Identification of indirect effects. Consistent estimation of the indirect effects via bank and migration networks relies on identification assumptions similar to those of shift-share instrumental variable regressions. Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020) discuss conditions for consistent estimation in shift-share research designs that combine a set of shocks with exposure shares. Our setting most closely matches the framework described in Borusyak et al. (2022), where identification relies on shocks that are as-good-as-randomly assigned across locations but variation in exposure shares can be endogenous.¹⁶

As shown in Section III.A, changes in excess dryness in origin municipalities are only determined by changes in temperature and rainfall during the 2001-2010 period relative to historical averages, and are uncorrelated with baseline municipality characteristics. We think of these as plausibly exogenous shocks. On the other hand, the levels of exposure shares—the weights ω_{bo} and w_{bm} in equations (38) and (39), and the migration shares α_{om} in equation (40)—are likely to be endogenous to municipality characteristics. We construct time-invariant weights using data on bank branch locations and migration flows

¹⁶In particular, Borusyak et al. (2022) show that a shift-share IV strategy leads to consistent estimates under (i) quasi-random shock assignment and (ii) many uncorrelated shocks. The latter implies that the number of shock observations grows with sample size, which is the case in our setting where shocks are observed at the municipality level.

that predate the period under study, in order to ensure that variation in weights does not capture endogenous changes during the 2001 to 2010 period.

Spatial correlation. A third concern is spatial correlation. In Figure II, 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 that excess dryness is spatially correlated across municipalities. We take several steps in the empirical analysis to address this concern. First, we show that results are robust to absorbing macroregion-specific trends, as shown in equation (37). 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 through both labor and capital markets. This is key to deal with spatial correlation as argued by Borusyak et al. (2023): empirical estimates of the effects of local shocks that do not account for spillovers to connected regions suffer from attenuation bias whenever shocks are spatially correlated.

Separating direct and indirect effects. There are two key empirical challenges when attempting to separately identify 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—migrant networks and capital networks—might themselves be geographically correlated.

Our strategy to deal with spatial correlation between shocks and indirect exposure measures is twofold. First, we use economic theory and detailed data to assess whether we can empirically separate direct and indirect effects. For example, we show that the direct effect of dryness generates 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 (Kennan and Walker 2011). Second, when we construct indirect exposure measures, we exclude areas within a 55km radius from each municipality. This is because the SPEI dataset is a grid with spatial resolution of 0.5° ($55\text{km} \times 55\text{km}$), and this exclusion ensures that our measures of indirect exposure do not capture dryness recorded in municipalities within the same SPEI grid cell. All our results are quantitatively similar if we remove this adjustment or use an alternative measure excluding areas within a larger 111km radius (1°), as shown in the Appendix. Indeed, estimates become less noisy as we remove nearby locations from indirect exposure measures, consistent with this spatial adjustment lowering the correlation between direct and indirect measures.

Regarding the correlation between different types of networks, Table B1 shows that

the correlation between indirect exposure via labor and capital markets is low (0.157), suggesting that the two measures capture different networks. This is likely because bank branch networks are based on common ownership by the same bank and are 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 affect both migration costs and goods trade costs, so our measure of indirect effects through labor market integration could be capturing spillovers through goods markets. For this reason, we control for a market access measure in the spirit of Donaldson and Hornbeck (2016). 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.¹⁷

IV RESULTS

This section presents our main empirical findings. The model in Section II predicts that climate-induced productivity shocks generate: (i) direct effects on employment and credit in affected regions; (ii) indirect effects via capital markets, as shocks propagate through bank branch networks, and (iii) indirect effects via labor markets, as workers migrate through pre-existing networks. We test these predictions by estimating equation (37). We begin by documenting the direct effect of excess dryness on agricultural production (Section IV.A). We then analyze the direct and indirect effects of this climate-induced productivity shock on capital and labor allocation (Section IV.B and IV.C).

IV.A THE EFFECTS OF EXCESS DRYNESS ON AGRICULTURE

We first establish that excess dryness reduces agricultural production. We consider two main outcome variables: area planted and value of 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. We show results separately for all crops and for the ten largest crops by area planted, which were consistently covered by the PAM survey during the period under study and collectively represent 88% of area

¹⁷The trade cost is based on the bilateral traveling cost via the Brazilian highway network in the year 2000 following Astorga (2019). The traveling costs c_{om} are obtained by dividing Brazil in grid cells and applying the fast marching method algorithm to determine the most efficient route between each pair of municipalities under the assumption that crossing a cell without a federal highway has a traveling cost 3.5 times higher than one with a federal highway. As in Allen and Arkolakis (2014), we then compute trade cost as the exponential form $\tau_{om} = \exp(c_{om})$. For the trade elasticity θ , we use the estimate of 3.39 by Astorga (2019).

farmed in the average municipality.¹⁸

Panel A of Table II reports the results of estimating a panel regression at municipality-year level of agricultural outcomes on excess dryness for the period 2000 to 2018. 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 excess dryness. A municipality moving from the median to the 90th percentile experiences a 5 percent decline in area harvested and value of agricultural production. These results are robust to including macro-region specific trends and municipality baseline controls interacted with year fixed effects. Overall, these estimates confirm that excess dryness relative to usual meteorological conditions causes sizable output losses in the agricultural sector.

We also document that the reduction in agricultural output is non-linear in the level of excess dryness. Figure V shows that municipalities in the top decile of the distribution of excess dryness suffer a loss of 14 percent in the value of production relative to those in the middle of the distribution, while municipalities in the bottom decile experience no significant change. This indicates that while extremely dry 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.

Long-run effects. In Panel B of Table II, we study the long-run effects of persistent excess dryness. The outcome variable is the long-run change in agricultural outcomes observed in a given municipality between the year 2000 and the year 2018, while the explanatory variable $\Delta Dryness_{m,2001-2018}$ captures the change between the average dryness experienced during the 2001 to 2018 period and the dryness experienced during the reference period 1901-1999. We find that a prolonged period of excess dryness relative to historical averages has large, negative and significant effects on agricultural production. A municipality moving from the median to the 90th percentile of excess dryness relative to its historical average experienced declines in area farmed of about 15%-20% and in total value of production of more than 20% over the last two decades. The fact that long-run declines in agricultural area and value of production are of similar or even larger magnitude than those observed in the yearly panel specification suggests limited adaptation responses to long run changes in dryness by the agricultural sector.

IV.B THE EFFECTS OF EXCESS DRYNESS ON CAPITAL ALLOCATION

We now examine how climate shocks propagate through bank branch networks. To test these predictions, we use data on loans, deposits, and net capital flows from the ESTBAN dataset of the Central Bank of Brazil, which reports balance sheet information

¹⁸The survey covers the major temporary and permanent crops farmed in Brazil, including information on area planted, area harvested and value of production. The ten largest crops by area planted include soybean, maize, sugar, wheat, rice, beans, cotton, coffee, cassava and potato.

at branch level for all commercial banks operating in the country.¹⁹ Net capital flows are constructed as loans originated by local bank branches minus deposits in those same branches, normalized by assets. 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.

Short-run effects Before presenting the long-run results from equation (37), we document short-run dynamics using a panel specification at the municipality-year level that shed light on how bank networks transmit climate shocks.

The results of this panel regression are summarized in Figure IV (a) and (b) and reported in detail in Table III. Regions suffering abnormally dry conditions in a given year experience an increase in agricultural loans financed by capital inflows [Figure IV (a)]. A municipality moving from the median to the 90th percentile of excess dryness experiences a 3.9 percent larger increase in loans and a 1.6 percentage points larger net *inflow* of capital as a share of local bank assets. As shown in columns (4) and (5), these loans are mostly directed to the agricultural sector. In turn, regions indirectly connected through the bank network—those with high values of $Exposure^K$ as defined in equation (39)—experience capital outflows and a reduction in loans [Figure IV (b)]. This pattern is consistent with a consumption smoothing motive: individuals and firms in agriculture perceive negative weather shocks as temporary reductions in income and borrow against future earnings, while connected regions provide insurance by funding the increase in lending.

Figure V (b) and (c) show that the increase in lending and net inflow of credit in directly affected regions is concentrated in the higher deciles of excess dryness. As documented in Figure V (a), these are the regions that also experience the largest declines in the value of agricultural production.

Overall, the documented short-run effects are consistent with the following mechanism: when regions experience drought shocks, local borrowers increase demand for credit to smooth consumption and maintain operations. Banks operating in these regions extend more loans, funded by capital inflows from their branches in other locations. This insurance provision exposes banks to climate risk. When shocks persist, loan defaults increase and bank liquidity falls, which may lead to credit contractions throughout the bank’s branch network.

Long-run effects. We now turn to our main specification, estimating equation (37) with long-run changes in credit outcomes between 2000 and 2010 as the dependent variable. The results are summarized in Figure IV (c) and (d) and reported in detail in Table IV.

¹⁹Loans and deposits of both firms and individuals are reported together in the ESTBAN data. This has the advantage of including loans to individual farmers running their farms and the disadvantage of pooling together production and consumption loans.

The coefficient β_1 on the direct effect shows that a municipality moving from the median to the 90th percentile of average excess dryness over the 2001 to 2010 period experienced a 17.7 percent decline in the balance of outstanding loans originated by local branches. This result is robust to adding measures of indirect exposure via banks ($Exposure^K$) and migrants ($Exposure^L$), as well as municipality-level controls, as shown in columns (2) and (3). 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.

The coefficient β_2 on the indirect effect via bank networks ($Exposure^K$) shows that regions exposed to excess dryness via banks also experience a significant decline in total lending. The magnitude indicates a relative decline in lending of about 4.6% for a municipality moving from the median to the 90th percentile of exposure.

Interpretation through the lens of the model. These findings are consistent with the credit disruption channel embedded in our model. Recall from Section II that credit supply in location l depends on the matrix SN , which captures how shocks propagate through bank branch networks. When drought-affected regions cannot repay loans extended during the short-run insurance phase, banks experience liquidity shocks.²⁰ If there are frictions in the interbank market, banks reduce lending throughout their branch network, including in regions not directly affected by excess dryness.²¹

IV.C THE EFFECTS OF EXCESS DRYNESS ON LABOR ALLOCATION

We now examine how climate shocks propagate through migration networks. The model predicts that when origin regions experience negative productivity shocks, workers migrate toward destinations with pre-existing migrant networks, increasing labor supply in those locations. We estimate equation (37) using long-run changes in employment and migration flows as outcomes.

Employment. We study the direct and indirect effects of excess dryness on the change in total employment between 2000 and 2010. Total employment is sourced from the Population Census, which is carried out by the IBGE at 10-year intervals. Census data allows us to observe both formal and informal workers, which is particularly important when studying the impact of excess dryness on the agricultural sector, characterized by high levels of informality.

²⁰For evidence consistent with this mechanism, see Aguilar-Gomez et al. (2022), which documents that increases in extremely hot days predict higher loan defaults by local firms using data from Mexico.

²¹The banking literature has highlighted that for liquidity shocks to propagate within bank branch networks, two frictions are necessary: (i) banks must have imperfect access to external financing; (ii) information frictions must channel credit to locations where banks have an informational advantage, such as locations where they have existing branches. Evidence on how liquidity shocks propagate within bank internal capital markets via branch networks has been shown in Bustos et al. (2020) for Brazil and Gilje et al. (2016) for the US.

The results are reported in Table V. The coefficient β_1 on the direct effect in column (1), which excludes indirect exposure measures, shows a negative employment effect of 1.1 percent for a municipality moving from the median to the 90th percentile of excess dryness. When including measures of indirect exposure, this effect doubles to 2.1 percent, as shown in column (4). This pattern confirms the attenuation bias predicted by Borusyak et al. (2023): when shocks are spatially correlated and spillovers are ignored, the direct effect is biased toward zero.

The coefficient β_2 on the indirect effect via migration networks ($Exposure^L$) shows that a municipality at the 90th percentile of exposure to dryness via migrants experiences a 1.3 percent *increase* in total employment relative to one at the median. This positive indirect effect is consistent with the model’s prediction that migrant networks channel workers from shock-affected origins toward destinations with pre-existing migrant networks.

The coefficient β_2 on the indirect effect via bank networks ($Exposure^K$) shows that regions connected via banks experience a *negative* employment effect. This finding is consistent with the net outflow of capital from connected regions documented in Table IV. Thus, the two channels of spatial integration generate opposite effects on destination employment: the migration network brings workers and increases employment, while the bank network transmits credit shocks and reduces employment.

We report direct and indirect effects of excess dryness on average wages in Appendix Table B3, 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 workers migrating out of affected regions were those earning relatively lower wages at baseline.

Migration. We shed light on the mechanisms behind the employment results by investigating the direct and indirect effects of excess dryness on migration flows. Census respondents report 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 and 2010, then aggregate by destination and origin to obtain total outflows and inflows for each municipality. We compute the rate of net migrant flows as:

$$netflows_{m,2005-2010} = \frac{in-migration_{m,2005-2010} - out-migration_{m,2005-2010}}{population_{m,2010}}.$$

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

The key findings are summarized in Figure VI and reported in detail in Table VI. The coefficient on the direct effect shows that a municipality moving from the median to the 90th percentile of excess dryness experiences a 1.2 percentage points larger net *outflow* of migrants as a share of its population. The indirect effect via migration networks

shows that a municipality moving from the median to the 90th percentile of $Exposure^L$ experiences a 0.6 percentage points larger net *inflow* rate of migrants.

These results directly test the model’s prediction about labor reallocation. In the model, workers from shock-affected origins migrate toward destinations where previous migrants from the same origin have settled, following pre-existing networks that reduce migration costs. The decomposition of net flows in Figure VI confirms this mechanism: the negative direct effects are mainly driven by increased outflows from affected regions (column 5), while the positive indirect effects are mainly driven by increased inflows into connected regions (column 6). Workers displaced by climate shocks do not disperse randomly across space; they flow toward destinations connected through the migration network F/M .²²

V CONCLUDING REMARKS

This paper develops a spatial equilibrium model that integrates bank branch networks and migration networks to study how climate shocks propagate across space, and tests its predictions using data on capital and labor flows across Brazilian municipalities. Our findings highlight the dual role of the banking sector in transmitting climate shocks. In the short run, bank branch networks provide insurance to drought-affected regions by channeling capital inflows from connected areas. However, when shocks persist, this mechanism reverses: loan defaults reduce bank liquidity and generate credit contractions throughout the branch network, producing negative spillovers from agricultural shocks to the broader economy in other regions.

The finding that interbank market frictions propagate agricultural shocks to credit markets in other regions highlights the importance of incorporating financial frictions in quantitative spatial models used to evaluate climate change costs. On the labor side, the fact that migration networks effectively channel displaced workers suggests that policies facilitating labor market matching at destination may enhance adaptation to climate change.

²²Consistent with the documented effects on net migration flows, Table B3 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. The positive indirect effect via migrants is partially mitigated by the negative indirect effect via banks, consistent with our findings on lending and employment.

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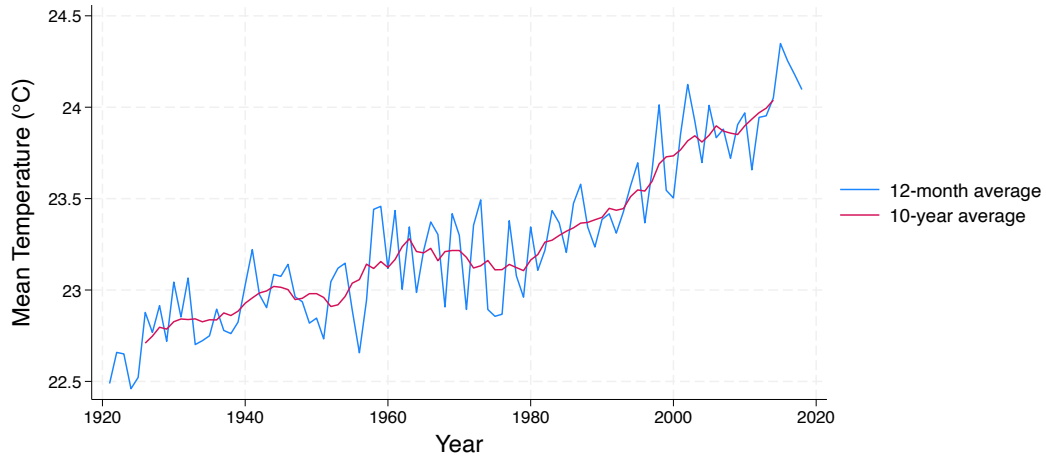
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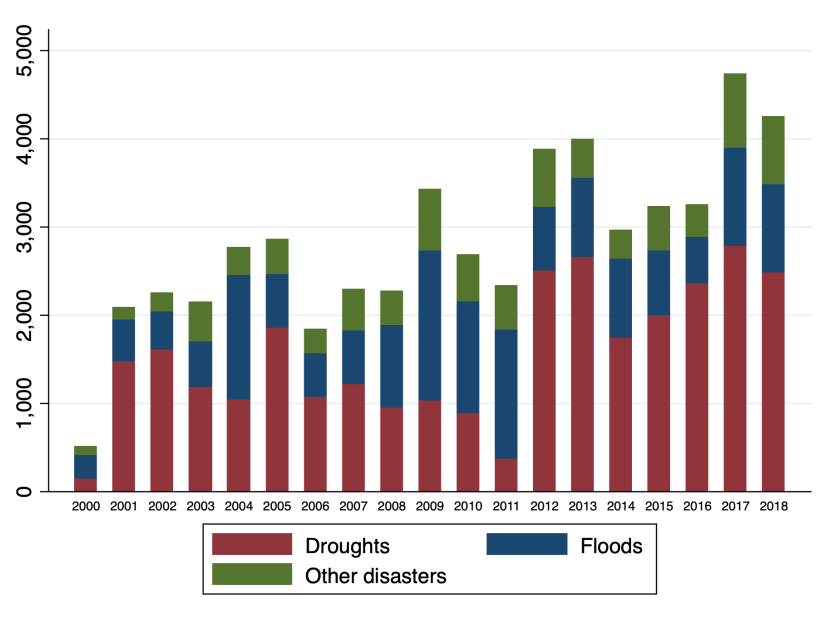
FIGURES

FIGURE I: CLIMATE PATTERNS IN BRAZIL

(a) Average temperature since 1920

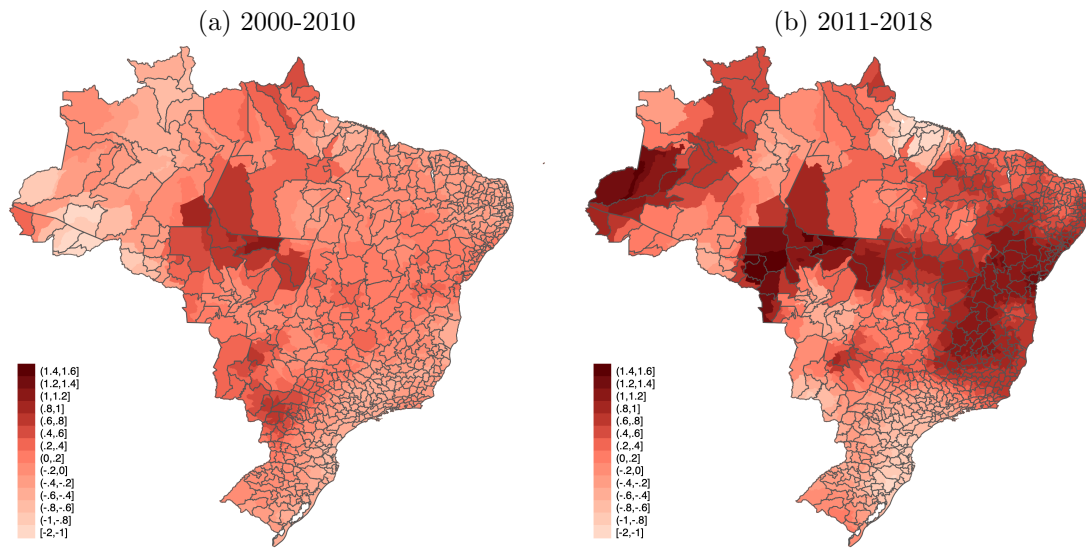


(b) Reported Natural Disasters: 2000-2018



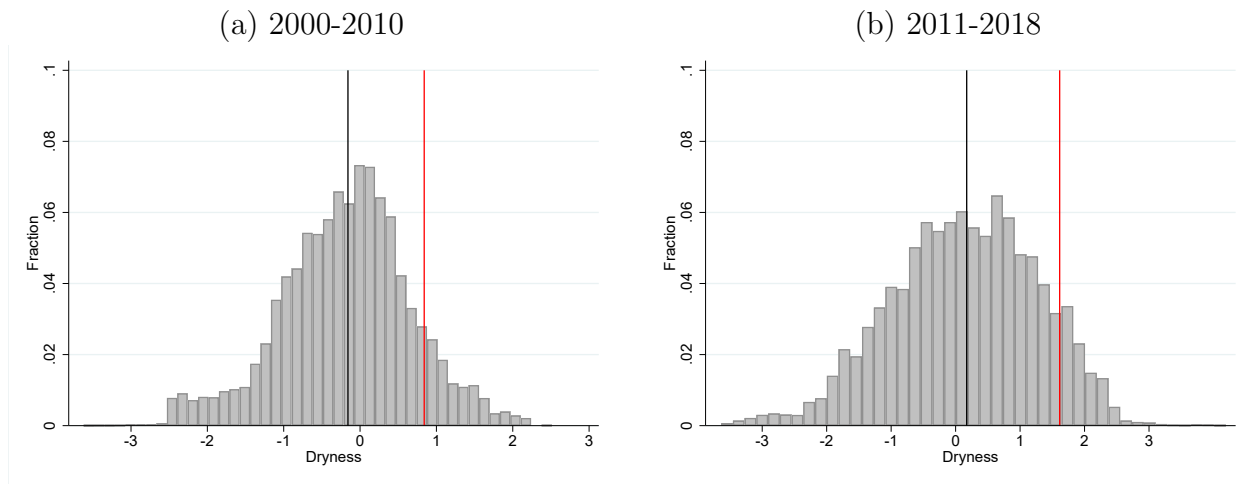
Source: Climatic Research Unit, University of East Anglia. Sistema Nacional de Proteção e Defesa Civil - SINPDEC

FIGURE II: GEOGRAPHICAL DISTRIBUTION OF Δ DRYNESS



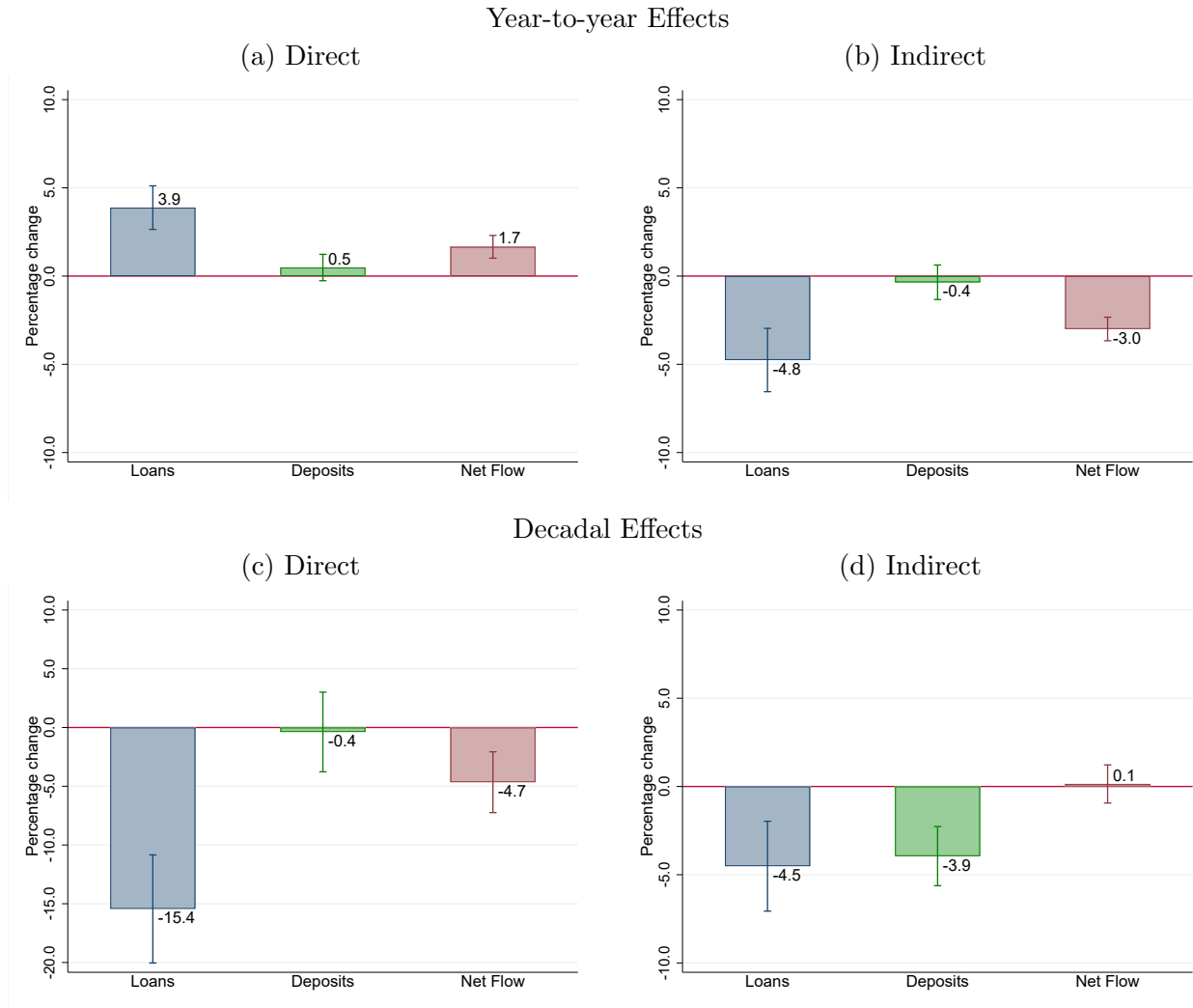
Notes: Maps show the excess dryness index (average SPEI in deviations from previous century multiplied by -1) during the indicated time period as well as the borders of the 558 microregions of Brazil, the level of clustering of standard errors used in the empirical analysis to account for spatial correlation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

FIGURE III: DISTRIBUTION OF Δ DRYNESS ACROSS MUNICIPALITIES



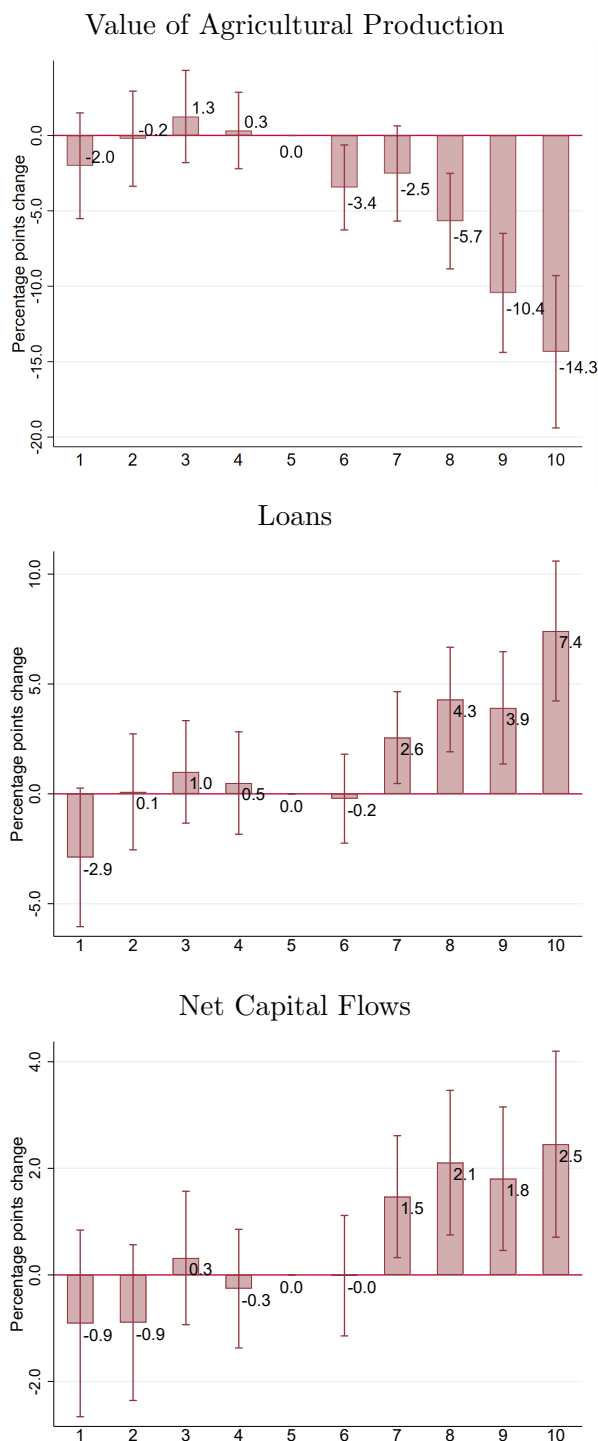
Notes: The figure shows the distribution of $\Delta Dryness$ across Brazilian municipalities by decade. The black line in both graphs represents the 50th percentile of the distribution, while the red line in both graphs represents the 90th percentile of the distribution. Quantifications in the paper are computed for a municipality moving from the 50th to the 90th percentile of excess dryness. This corresponds to 1.17 standard deviations of excess dryness in the 2000-2010 decade, and to 1.28 standard deviations in the 2011-2018 decade.

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



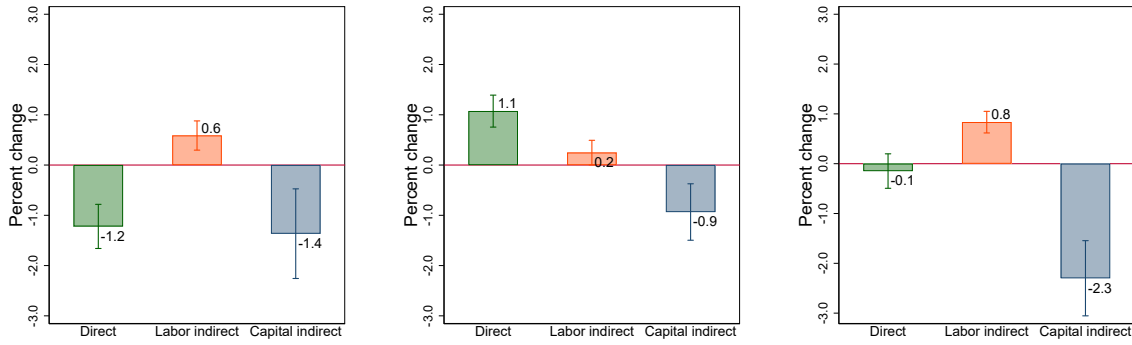
Notes: The figure reports the estimated effects (in percentage points) on capital outcomes for a municipality going from the 50th to the 90th percentile in the direct and indirect (exposure via banks) measures of excess dryness. Panels (a) and (b) report the results for the year-to-year effect of dryness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

FIGURE V: DIRECT EFFECTS OF EXCESS DRYNESS ON AGRICULTURAL PRODUCTION, BANK LOANS AND CAPITAL FLOWS BY DECILE OF DRYNESS



Notes: The figure shows the estimated coefficients on dummies capturing deciles of the excess dryness index in a panel regression at municipality-year level where the outcome variables are: (a) log value of agricultural production (b) log value of outstanding loan balance and (c) net flows (loans minus deposits) normalized by assets in local branches. Deciles of *Dryness* go from the wettest to the driest. Estimated effects are relative to the 5th decile. Controls include AMC fixed effects, macro-region times year fixed effects and the share of population living in rural areas, log income per capita, literacy rate, population density, deforestation and changes in soy and maize potential yields, each interacted with year dummies. Vertical lines are 95 percent confidence intervals.

FIGURE VI: EFFECTS OF EXCESS DRYNESS ON 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.

TABLES

TABLE I: BALANCE TEST

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

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

TABLE II: THE EFFECT OF EXCESS DRYNESS ON AGRICULTURAL OUTCOMES

	(1)	(2)	(3)	(4)
VARIABLES	log area planted all crops	log area planted top 10 crops	log value production all crops	log value production top 10 crops
Dryness	-0.0481*** (0.00748)	-0.0556*** (0.00887)	-0.0403*** (0.00837)	-0.0632*** (0.0111)
Observations	79,160	79,160	79,160	79,160
R-squared	0.937	0.926	0.925	0.906
AMC and year FE	y	y	y	y
Region x year FE	y	y	y	y
Controls x year FE	y	y	y	y

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

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

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

VARIABLES	(1) log loans all	(2) log loans all	(3) log loans all	(4) agri	(5) non-agri	(6) log deposits	(7) net flows
Dryness	0.0382*** (0.00705)	0.0497*** (0.00780)	0.0388*** (0.00749)	0.0775*** (0.0152)	0.0192** (0.00749)	0.00483 (0.00454)	0.0166*** (0.00391)
Exposure to Dryness via banks		-0.0407*** (0.0112)	-0.0476*** (0.0109)	-0.145*** (0.0279)	-0.0284*** (0.00923)	-0.00351 (0.00594)	-0.0300*** (0.00405)
Observations	58,177	53,696	53,658	46,773	53,658	53,658	53,658
R-squared	0.958	0.959	0.961	0.880	0.967	0.980	0.793
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 IV: DECADAL EFFECT OF DRYNESS ON CAPITAL OUTCOMES
2000-2010

VARIABLES	(1) $\Delta \log$ loans all	(2) $\Delta \log$ loans all	(3) $\Delta \log$ loans all	(4) $\Delta \log$ loans all	(5) $\Delta \log$ deposits	(6) net flows
Δ Dryness, 2001-2010	-0.106*** (0.0239)	-0.103*** (0.0238)	-0.154*** (0.0279)	-0.177*** (0.0308)	0.0130 (0.0215)	-0.0728*** (0.0170)
Exposure to Δ Dryness via banks		-0.0437*** (0.0155)	-0.0452*** (0.0154)	-0.0461*** (0.0155)	-0.0388*** (0.0101)	0.000346 (0.00649)
Exposure to Δ Dryness via migrants			0.0843*** (0.0242)	0.0819*** (0.0243)	0.0212 (0.0161)	0.0155 (0.0134)
Observations	2,795	2,795	2,795	2,795	2,795	2,795
R-squared	0.170	0.176	0.181	0.182	0.206	0.072
Macro FE	y	y	y	y	y	y
Controls	y	y	y	y	y	y
Exposure via Goods Market	n	n	n	y	y	y

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

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

VARIABLES	(1)	(2)	(3)	(4)
Δ Dryness, 2001-2010	-0.0112* (0.00607)	-0.0188*** (0.00717)	-0.0194*** (0.00721)	-0.0208** (0.00806)
Exposure to Δ Dryness via migrants		0.0121** (0.00581)	0.0130** (0.00584)	0.0130** (0.00582)
Exposure to Δ Dryness via banks			-0.00411* (0.00217)	-0.00414* (0.00217)
Observations	4,248	4,247	4,247	4,247
R-squared	0.128	0.130	0.131	0.131
Macro-region FE	y	y	y	y
Controls	y	y	y	y
Exposure via Goods Market	n	n	n	y

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

TABLE VI: MIGRATION FLOWS
2005-2010

VARIABLES	(1) net flows	(2) net flows	(3) net flows	(4) net flows	(5) outflow	(6) inflow
Δ Dryness, 2001-2010	-0.0112*** (0.00220)	-0.0145*** (0.00260)	-0.0148*** (0.00256)	-0.0122*** (0.00267)	0.0107*** (0.00193)	-0.00148 (0.00210)
Exposure to Δ Dryness via migrants		0.00541*** (0.00175)	0.00586*** (0.00175)	0.00587*** (0.00177)	0.00247* (0.00149)	0.00834*** (0.00132)
Exposure to Δ Dryness via banks			-0.00208** (0.000814)	-0.00203** (0.000803)	-0.00139*** (0.000506)	-0.00341*** (0.000680)
Observations	4,248	4,247	4,247	4,247	4,247	4,247
R-squared	0.221	0.224	0.226	0.229	0.211	0.304
Macro-region FE	y	y	y	y	y	y
Controls	y	y	y	y	y	y
Exposure via Goods Market	n	n	n	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.

Online Appendix for:
“Climate Change and Spatial Capital Reallocation”

A EXCESS DRYNESS AND REPORTED DROUGHTS.

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

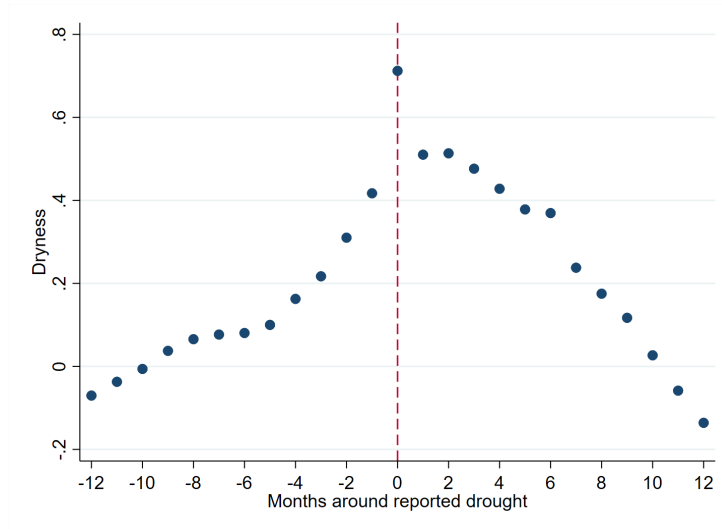
$$Dryness_{mt} = \alpha + \sum_{k=-12}^{12} \beta_k drought_{lt}^k + \varepsilon_{lt}, \quad (A1)$$

where l indexes municipalities, t indexes calendar months, and k indexes months relative to a reported drought in the SINPDEC data. The variable $drought_{lt}^k$ is a dummy equal to 1 if municipality l 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 A1 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 a panel specification at municipality-year level 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*. We report coefficient estimates for this specification in Table A1. 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.

FIGURE A1: AVERAGE EXCESS DRYNESS INDEX AROUND DROUGHT EVENTS



Notes: The figure shows the β_k coefficients estimated using equation A1. We plot the coefficients on the 12 leads and 12 lags of the dummy *drought*, using monthly data at the municipality level from 2000 to 2018.

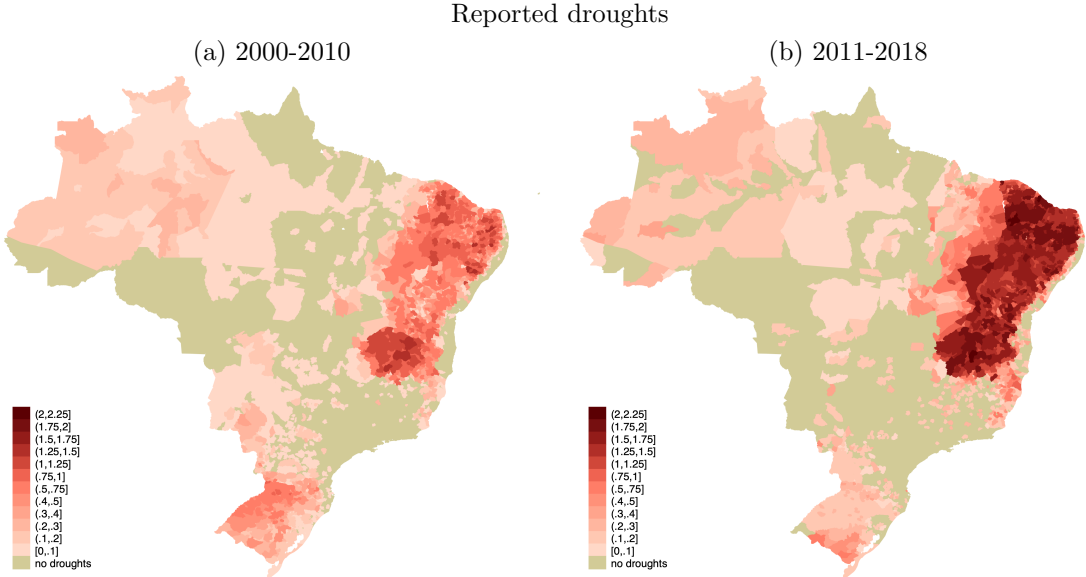
TABLE A1: REPORTED DROUGHTS AND EXCESS DRYNESS

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

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

B ADDITIONAL FIGURES AND TABLES

FIGURE C1: GEOGRAPHICAL DISTRIBUTION OF REPORTED DROUGHTS



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

TABLE B1: CORRELATION BETWEEN DIRECT AND INDIRECT EXPOSURE

	Dryness	Exposure via migrants	Exposure via banks
Dryness	1.000		
Exposure via migrants	0.299 (0.017)	1.000	
Exposure via banks	0.207 (0.018)	0.412 (0.017)	1.000

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

TABLE B2: COEFFICIENTS WITH NON-NORMALIZED DIRECT AND INDIRECT EFFECTS
FOR MODEL PARAMETERS

VARIABLES	(1) $\Delta \log \text{ loans}$	(2) $\Delta \log \text{ employment}$
$\Delta \text{ Dryness, 2001-2010}$	-0.337*** (0.0584)	-0.0394** (0.0153)
Exposure to $\Delta \text{ Dryness}$ via banks	-0.311*** (0.105)	
Exposure to $\Delta \text{ Dryness}$ via migrants	0.485*** (0.144)	0.0769** (0.0344)
Exposure to $\Delta \text{ Dryness}$ via banks (with zeros)		-0.0279* (0.0146)
Observations	2,795	4,247
R-squared	0.182	0.131
Macro-region FE	y	y
Controls	y	y
Exposure via Goods Market	y	y

Notes:

TABLE B3: DECADAL EFFECT OF DRYNESS ON POPULATION AND WAGES
2000-2010

VARIABLES	(1) $\Delta \log \text{Pop}$	(2) $\Delta \log \text{wage}$
$\Delta \text{Dryness, 2001-2010}$	-0.0428*** (0.00661)	0.00637 (0.00813)
Exposure to $\Delta \text{Dryness}$ via migrants	0.0168*** (0.00460)	0.0138** (0.00644)
Exposure to $\Delta \text{Dryness}$ via banks	-0.00383** (0.00177)	0.000788 (0.00239)
Observations	4,247	4,247
R-squared	0.210	0.168
Macro-region FE	y	y
Controls	y	y
Exposure via Goods Market	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 $\Delta \text{Dryness}$ via road network. In the wage regression 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.

C THEORETICAL DERIVATIONS

C.A EXACT SOLUTION FOR EXTENDED MODEL WITH LABOR MOBILITY

This appendix sections derives the exact solution for wages, loan rates, employment, and borrowing starting from the four equilibrium conditions. Throughout, hats denote log changes and all objects are $L \times 1$ vectors unless noted otherwise. Let $G \equiv SN'$.

Equilibrium conditions. The log-linearized equilibrium conditions is characterized by the following four equations:

$$\hat{\mathbf{L}} = A_L \hat{\mathbf{w}}, \quad A_L \equiv \theta(I - \Gamma' \Pi), \quad (\text{A1})$$

$$\hat{\mathbf{L}} = (\sigma - 1)\gamma \hat{\mathbf{C}} - \sigma \hat{\mathbf{w}} - \sigma \tilde{k} \hat{\mathbf{R}}, \quad (\text{A2})$$

$$\hat{\mathbf{B}} = \theta_B(I - G)\hat{\mathbf{R}} + \beta G\hat{\mathbf{C}}, \quad (\text{A3})$$

$$\hat{\mathbf{B}} = \hat{\mathbf{w}} + (1 + \psi)\hat{\mathbf{L}}. \quad (\text{A4})$$

Step 1: eliminate $\hat{\mathbf{L}}$ and $\hat{\mathbf{B}}$. Using (A1) in (A4) gives

$$\hat{\mathbf{B}} = \hat{\mathbf{w}} + (1 + \psi)A_L \hat{\mathbf{w}} = (I + (1 + \psi)A_L) \hat{\mathbf{w}}. \quad (\text{A5})$$

Using (A1) in (A2) gives a relation between $(\hat{\mathbf{w}}, \hat{\mathbf{R}})$:

$$A_L \hat{\mathbf{w}} = (\sigma - 1)\gamma \hat{\mathbf{C}} - \sigma \hat{\mathbf{w}} - \sigma \tilde{k} \hat{\mathbf{R}} \iff (\sigma I + A_L) \hat{\mathbf{w}} + \sigma \tilde{k} \hat{\mathbf{R}} = (\sigma - 1)\gamma \hat{\mathbf{C}}. \quad (\text{A6})$$

Finally, substitute (A5) into the loan-supply equation (A3):

$$(I + (1 + \psi)A_L) \hat{\mathbf{w}} = \theta_B(I - G)\hat{\mathbf{R}} + \beta G\hat{\mathbf{C}}. \quad (\text{A7})$$

Step 2: solve for $(\hat{\mathbf{w}}, \hat{\mathbf{R}})$ as a linear system. Stacking (A6)–(A7) yields the $2L \times 2L$ block system

$$\begin{pmatrix} \sigma I + A_L & \sigma \tilde{k} I \\ I + (1 + \psi)A_L & -\theta_B(I - G) \end{pmatrix} \begin{pmatrix} \hat{\mathbf{w}} \\ \hat{\mathbf{R}} \end{pmatrix} = \begin{pmatrix} (\sigma - 1)\gamma \hat{\mathbf{C}} \\ \beta G\hat{\mathbf{C}} \end{pmatrix}. \quad (\text{A8})$$

Since the block matrix in (A8) is generically invertible, this pins down a unique solution.

It is convenient to solve by eliminating one price, for example $\hat{\mathbf{R}}$. From (A7),

$$\hat{\mathbf{R}} = \theta_B^{-1}(I - G)^{-1} \left[(I + (1 + \psi)A_L) \hat{\mathbf{w}} - \beta G\hat{\mathbf{C}} \right]. \quad (\text{A9})$$

Substitute (A9) into (A6) and collect terms in $\hat{\mathbf{w}}$:

$$(\sigma I + A_L) \hat{\mathbf{w}} + \sigma \tilde{k} \theta_B^{-1}(I - G)^{-1} (I + (1 + \psi)A_L) \hat{\mathbf{w}} = (\sigma - 1)\gamma \hat{\mathbf{C}} + \sigma \tilde{k} \theta_B^{-1}(I - G)^{-1} \beta G\hat{\mathbf{C}}. \quad (\text{A10})$$

Define the $L \times L$ matrix

$$\mathcal{M} \equiv (\sigma I + A_L) + \sigma \tilde{k} \theta_B^{-1} (I - G)^{-1} (I + (1 + \psi) A_L). \quad (\text{A11})$$

Then (A10) becomes $\mathcal{M} \hat{\mathbf{w}} = \text{RHS}$, so

$$\hat{\mathbf{w}} = \mathcal{M}^{-1} \left[(\sigma - 1) \gamma \hat{\mathbf{C}} + \sigma \tilde{k} \theta_B^{-1} (I - G)^{-1} \beta G \hat{\mathbf{C}} \right]. \quad (\text{A12})$$

Step 3: recover $\hat{\mathbf{R}}$, $\hat{\mathbf{L}}$, and $\hat{\mathbf{B}}$. Given $\hat{\mathbf{w}}$, the remaining variables follow directly:

$$\hat{\mathbf{R}} = \theta_B^{-1} (I - G)^{-1} \left[(I + (1 + \psi) A_L) \hat{\mathbf{w}} - \beta G \hat{\mathbf{C}} \right], \quad (\text{A13})$$

$$\hat{\mathbf{L}} = A_L \hat{\mathbf{w}}, \quad (\text{A14})$$

$$\hat{\mathbf{B}} = (I + (1 + \psi) A_L) \hat{\mathbf{w}} = \hat{\mathbf{w}} + (1 + \psi) \hat{\mathbf{L}}. \quad (\text{A15})$$

Summary Equations (A12)–(A15) give the exact log-linear solution for equilibrium wages, loan rates, employment, and borrowing in terms of primitives $(A_L, G, \sigma, \theta_B, \tilde{k}, \beta, \gamma, \psi)$ and the shock vector $\hat{\mathbf{C}}$.

C.B FIRST-ORDER APPROXIMATION OF THE MODEL WITH LABOR MOBILITY

We start from the labor and credit demand and supply equations, and derive the equilibrium outcomes from these four equations, spelling out the exact assumptions we do to simplify matrix inversions.

Let $G \equiv SN'$. The equilibrium conditions in hat algebra are:

$$\hat{\mathbf{L}} = A_L \hat{\mathbf{w}}, \quad A_L \equiv \theta (I - \Gamma' \Pi), \quad (\text{A16})$$

$$\hat{\mathbf{L}} = (\sigma - 1) \gamma \hat{\mathbf{C}} - \sigma \hat{\mathbf{w}} - \sigma \tilde{k} \hat{\mathbf{R}}, \quad (\text{A17})$$

$$\hat{\mathbf{B}} = \theta_B (I - G) \hat{\mathbf{R}} + \beta G \hat{\mathbf{C}}, \quad (\text{A18})$$

$$\hat{\mathbf{B}} = \hat{\mathbf{w}} + (1 + \psi) \hat{\mathbf{L}}. \quad (\text{A19})$$

Approximation Assumptions We impose the following approximations. (i) Diffuse bank network: $(I - G)^{-1} \approx I + G$ and we neglect G^2 . (ii) Borusyak et al. (2023) mobility approximation: using $I - \Gamma' \Pi \approx -(\Delta \Gamma' + \Delta \Pi)$ and $(\Delta \Pi + \Delta \Gamma') x = -2 \mu (I - \mathcal{F}) x$ with $\mu = \text{diag}(M_l/L_l)$, we write $A_L x \approx 2 \theta \mu (I - \mathcal{F}) x$. (iii) First-round propagation: we keep $\mathcal{F} \hat{\mathbf{C}}$ and $G \hat{\mathbf{C}}$ but neglect $\mathcal{F} G \hat{\mathbf{C}}$.

The intuition for assumption (iii) is that the matrices F and SN' represent two distinct propagation mechanisms operating on large networks. The matrix F captures labor reallocation across locations through migration flows, while SN' captures credit reallocation across locations through shared bank exposure. In both cases, propagation occurs through weighted averages over many nodes, so that individual links carry little weight.

The term $SN'\hat{\mathbf{C}}$ therefore represents a first-round diffusion of climate shocks through the banking network, and $F\hat{\mathbf{C}}$ represents a first-round diffusion through labor mobility. The interaction $F SN'\hat{\mathbf{C}}$ corresponds to a second-round mechanism in which a shock is first transmitted through the banking network and then further propagated through labor re-allocation. Because each propagation step averages over many nodes, this second-round effect is quantitatively smaller than the direct first-round effects and can be neglected in a first-order approximation.

More formally, assumption (iii) can be justified as follows. Both F and SN' are row-stochastic matrices with nonnegative entries whose magnitudes are small when the number of locations or banks is large. In particular, each row of F sums to one and typically contains $O(L)$ nonzero entries of order $O(1/L)$, while each row of SN' contains $O(B)$ nonzero entries of order $O(1/B)$. Let $\|\cdot\|$ denote any operator norm compatible with the Euclidean norm. Under these conditions, both $\|F\|$ and $\|SN'\|$ are bounded by one, while the product satisfies

$$\|F SN'\| \leq \|F\| \|SN'\| < 1,$$

with entries of order $O(1/\min\{L, B\})$. As a result, for any bounded vector x , the magnitude of $F SN'x$ is second order relative to Fx and $SN'x$. Dropping the interaction term $F SN'\hat{\mathbf{C}}$ therefore corresponds to truncating the Neumann-series expansion of the equilibrium mapping at first order in the two network operators. This approximation isolates the dominant linear propagation channels while abstracting from higher-order feedback effects that operate through multiple successive network layers.

Derivations Under this first-round approximation, wages satisfy

$$\hat{\mathbf{w}} \approx \chi \hat{\mathbf{C}} + \xi G\hat{\mathbf{C}}, \tag{A20}$$

where

$$\chi = \frac{(\sigma - 1)\gamma \theta_B}{\sigma(\theta_B + \tilde{k})}, \tag{A21}$$

$$\xi = \frac{\tilde{k}}{\theta_B + \tilde{k}}\beta - \frac{\tilde{k}\theta_B}{(\theta_B + \tilde{k})^2} \frac{\sigma - 1}{\sigma}\gamma. \tag{A22}$$

Using $\hat{\mathbf{L}} = A_L \hat{\mathbf{w}}$ and $A_L x \approx 2\theta \mu (I - \mathcal{F})x$,

$$\hat{\mathbf{L}} \approx 2\theta \mu (I - \mathcal{F}) \left(\chi \hat{\mathbf{C}} + \xi G\hat{\mathbf{C}} \right) \tag{A23}$$

$$= 2\theta \mu \left[\chi \hat{\mathbf{C}} - \chi \mathcal{F}\hat{\mathbf{C}} + \xi G\hat{\mathbf{C}} - \xi \mathcal{F}G\hat{\mathbf{C}} \right]. \tag{A24}$$

Neglecting the interaction term $\mathcal{F}G\hat{\mathbf{C}}$ yields

$$\hat{\mathbf{L}} \approx (2\theta\chi)\mu\hat{\mathbf{C}} - (2\theta\chi)\mu\mathcal{F}\hat{\mathbf{C}} + (2\theta\xi)\mu G\hat{\mathbf{C}}. \quad (\text{A25})$$

Loan demand is $\hat{\mathbf{B}} = \hat{\mathbf{w}} + (1 + \psi)\hat{\mathbf{L}}$. Substituting the expressions for $\hat{\mathbf{w}}$ and $\hat{\mathbf{L}}$ gives

$$\hat{\mathbf{B}} \approx [\chi I + (1 + \psi)(2\theta\chi)\mu]\hat{\mathbf{C}} - (1 + \psi)(2\theta\chi)\mu\mathcal{F}\hat{\mathbf{C}} \quad (\text{A26})$$

$$+ [\xi I + (1 + \psi)(2\theta\xi)\mu]G\hat{\mathbf{C}}. \quad (\text{A27})$$

Finally, assuming that $M/L = \bar{m}I$ we have that we can factor out I from the coefficients and obtain the expressions in the main text, Equations (31) and (32).