Climate Change, Food Prices, and Inequality*

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Abstract

This paper examines how climate change will affect food prices across regions and people across the income distribution, emphasizing the uneven effects on agricultural productivity. As climate change shifts comparative advantages in food production, trade frictions limit adaptive sourcing. These frictions induce local sourcing, making food prices dependent on local productivity and increasing prices everywhere. Low-income households, with higher food expenditure shares, are particularly vulnerable to local food price increases. We develop a spatial macro trade model that incorporates income heterogeneity and two types of food goods with different trade frictions, allowing us to decompose welfare losses stemming from climate change into food expenditure shares, trade shares, and productivity changes. Using Brazilian data, we estimate intra-national trade shares using short-term weather shocks, price changes, and driving times between states. We find that trade frictions for fresh food are twice as sensitive to driving time relative to commodities, which face lower trade costs. Counterfactuals based on productivity forecasts indicate substantial welfare losses, with the lowest income decile in the most affected states willing to forgo 3% of income to avoid projected productivity declines. Improving road infrastructure could mitigate these effects, with low-income households in some states willing to pay up to 0.8% of their income for a 10% increase in the average driving speed.

JEL classification: E31, F16, O44, Q54, Q56.

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1 Introduction

Climate change is expected to reshape the spatial patterns of agricultural productivity. One adaptive strategy involves leveraging novel comparative advantages through the re-optimization of food sourcing. Nevertheless, due to the high costs associated with transporting goods over distances, trade barriers restrict the degree to which this process can happen. For items that incur substantial transportation costs, the significance of local productivity becomes paramount. With the rise in food prices, the welfare implications are not uniformly distributed across various income levels, as lower-income households usually spend a higher proportion of their budget on food.

What effects will climate change have on food prices and how will it influence individuals across various income levels? To address this question, we develop a spatial model of food production and trade, building on ? and ?. Our model incorporates rich heterogeneity in four dimensions. First, to examine the importance of trade ease, we distinguish between two types of food goods, each facing different trade costs. Second, locations vary in productivity for each type of food. Third, locations are distinct regarding their degree of connectedness to others. Fourth, income levels within each location vary, with both relatively richer and poorer households.

In our model, locations produce goods based on their productivity and engage in trade. Food goods face varying trade costs, which distort the comparative advantages of locations and influence trade patterns. Goods with higher trade costs exhibit a greater spatial price dispersion compared to those with lower trade costs. For high-trade-cost goods, local productivity is especially critical, as lower productivity leads to higher prices.

We calculate the welfare effects stemming from changes in food prices. In our setting, shifts in utility caused by climate change are driven solely by changes in food prices, as household income is constant. We decompose the equivalent variation from climate change into three components, drawing on standard demand theory. The first is the food expenditure share: poorer households, with higher food expenditure shares, are more sensitive to changes in food prices. The second is the trade shares between locations, which reflect how regions are affected by productivity changes in other regions they trade with, including themselves.

The third component captures changes in potential food productivity across different areas.

We apply the model to Brazil, treating each state as a separate location. Given Brazil's vast latitude range and tropical climate, there are significant productivity differences across regions and crops. The country's extensive land coverage and reliance on road-based transportation make the movement of goods challenging. Additionally, income inequality is pronounced both within and across states.

Trade flows and frictions are central to our model, but not directly observed in the data. This is a frequently encountered issue in domestic trade is the necessity for comprehensive information on trade flows among sub-national units, hardly observed in the data. As in many studies of intra-national trade, e.g, ?, ?, ?, the trade flows are not directly observable in data between Brazilian states[1]. To overcome this data constraint, we incorporate the model structure with the inclusion of short-term weather variances, allowing us to derive a correlation between price fluctuations and weather anomalies, both quantifiable in the data. We then employ this observed variation in prices and weather disturbances to extract estimates of these trade barriers for different types of food goods.

In our model, heat shocks reduce food productivity, driving up prices. Neighboring states are also affected, as they import food from the impacted state. Thus, the observed price change in any state reflects a weighted average of heat shocks between states, with the weights determined by trade shares. These shares depend on average potential productivity, labor costs, and bilateral trade frictions. To capture this structure, we combine a panel of Consumer Price Index (CPI) data with a panel of heat shocks. Drawing from crop science literature, e.g. ?, we focus on a temperature threshold of 30°C/86°F, known to harm crop yields. Using satellite weather data ?, we construct a panel tracking the number of hours (in days) that temperatures exceeded this threshold in each city. We leverage these heat shocks to estimate trade frictions from variations in prices and temperatures and validate the threshold by showing evidence of yield declines when crops are exposed to such temperatures during the growing season.

To the extent that most cargo transportation within Brazil rely on trucks via roads

[1]This feature is common across most countries. Canada is a noticeable exception, which releases inter-provincial trade flows. See, e.g., ?

(?), we model trade frictions as a function of driving time between states[2]. We build on a classification of food goods' tradability developed by the Brazilian Central Bank for tracking the CPI. Using this classification, we compute the price index for baskets of food products, in a panel of locations. One index includes goods that are frequently traded on the international market, such as commodities, while the other represents items that are less commonly traded globally, typically more perishable, fresh goods. We separately estimate the elasticity of trade costs with respect to the driving time for each basket. Our findings suggest that this elasticity is nearly double for goods with elevated trade costs, such as fresh goods, compared to those with reduced trade costs, such as commodities.

We examine how the spatial correlation of heat and price changes shape our results. While heat shocks naturally show positive spatial correlation, we document that a similar pattern for inflation dynamics across locations. Specifically, as driving time between locations increases, making them less connected, the inflation correlation decreases, especially for goods with higher trade costs. Our model capture this feature of the data: locations farther apart experience different heat shocks, and substantial trade frictions make local prices more dependent on nearby conditions. Thus, inflation correlations decline more sharply for high-trade-cost goods, with a more modest decline observed for low-trade-cost goods.

With these estimates of trade frictions and trade shares, we proceed to do counterfactual exercises. Actual production data often suffers from selection bias in Ricardian models, as locations tend to produce goods where they have a comparative advantage. Hence, the productivity across the spectrum of goods is latent: in the actual production data, we observe only partially these productivities. To address this, we use the potential productivity of crops across regions for each type of food good. Following our equivalent variation decomposition, we incorporate proportional changes in average potential productivity into the model. These estimates are sourced from the GAEZ project by ?, based on various climate change scenarios.

The GAEZ project also provides data on the historical levels of this potential productivity. We employ this historical data for two reasons. First, it serves as an input to recover trade frictions. Second, it provides a benchmark to compare with alternative productivity forecasts from the GAEZ project. In our equivalent variation decomposition, changes in

[2] ? shows data for 2021, with the estimated share of cargo transported by road is 66%. Railroads correspond to 18% and waterways other 15%.

average potential productivity are central, making historical estimates a crucial basis for comparison.

The GAEZ project provides detailed data on agricultural productivity under various climate change scenarios, covering different time horizons and intensities of productivity shifts linked to greenhouse gas concentrations. Given the higher uncertainty over longer horizons, we focus our results using the optimistic scenario (RCP 2.6) for the period ending in 2040[3].

We show that even under the most optimistic climate change scenario, there is significant variation in potential productivity changes across states compared to historical baselines. Furthermore, there is substantial heterogeneity in the effect of climate change on productivity between food types, with high-trade-cost foods experiencing more pronounced declines in average potential productivity.

Using our equivalent variation analysis, we estimate how much households would be willing to pay to avoid the productivity changes linked to climate change. While food prices are an aggregate at the state level, within-state income heterogeneity leads to differentiated welfare effects of price increases. Due to non-homothetic preferences, food expenditure shares decline with income, consistent with observed data. Households in the lowest income decile are more vulnerable to changes in food prices, as they allocate a larger share of their income to food[4]. Under the optimistic scenario, households in the first income decile in some states would be willing to forgo up to 3% of their income to avoid these productivity shifts.

Finally, we argue that an effective adaptation strategy is to improve road quality. Since trade frictions are modeled as a function of driving time between states, increasing average road speed effectively reduces trade barriers. We derive a formula for the equivalent variation under this scenario, involving three components similar to the productivity change decomposition: food expenditure shares, trade shares between states, and the estimated elasticity of trade frictions with respect to driving time. We find that, given these elasticities, the sufficient statistic for the equivalent variation is the own trade share of each state, linking to

[3]The GAEZ data employs four Representative Concentration Pathways (RCPs): 2.6, 4.5, 6.0, and 8.5 to construct scenarios. These values represent radiative forcing levels by 2100, reflecting greenhouse gas concentrations, with lower values indicating cooler temperatures and stricter mitigation policies.

[4]We show this pattern in figure ??.

findings from the international trade literature, (?). For a 10% improvement in road quality, households in the lowest income decile would be willing to pay up to 0.8% of their income under the optimistic scenario.

Related Literature. Our paper intersects several branches of the literature. A central component of our analysis is the recovery of trade cost estimates, given the lack of detailed intra-national trade flow data. There is a growing body of work focused on identifying and measuring intra-national trade costs. ? summarizes the main challenges of the task. Some papers infer and bound trade costs using observed price differentials across locations, leveraging their model structures(??). Others papers (?), ?) rely on the price differentials of some good produced by a monopolist or single factory to estimate trade costs, relating this dispersion to distance.

? uses price dispersion in coffee markets in Peru, together with road quality data, to measure trade frictions. Similarly to ?, the author assumes that trade friction is the same for all crops, depending only on the distance from the road. Focusing on Brazil, ? uses deviations in farm gate prices to estimate trade elasticities and the elasticity of trade costs with respect to driving time between locations. A related finding in this study is that the elasticity is twice as large for perishables relative to non-perishables, a result similar to ours, although we find a higher magnitude. Since we do not observe price levels, only changes in prices, we take a different approach to estimating trade frictions by using weather variability as a means to recover these estimates. Exploiting this link between weather shocks and prices changes is one of our contributions.

Our paper also contributes to the literature on the pass-through of shocks to prices. ? investigates the pass-through of the Swiss Franc's appreciation to consumer prices, while ? examines how trade costs affect the pass-through from exchange rate movements to consumer prices. ? uses a cross-country panel to assess the price dynamics of different consumption baskets after extreme weather events, such as sweltering summers or cold winters. We add to this literature by documenting increases in the local food prices following exposure to high temperatures, relying on detailed, disaggregate data for the temperatures.

We are also related to the literature on the economic effects of transitory weather shocks.

? documents declines in productivity and changes in labor supply in Indian factories exposed to high temperatures. ? shows how firms diversify their sourcing across regions to mitigate the risk of floods in India. ? investigates energy price variability and its disproportionate effects on low-income households' expenditure, studying the distributional impact of energy price shocks. In ?, we studied how migration flows from rural Guatemala to the US are affected by local temperature shocks. Similar to our approach here, we use short-run fluctuations in temperature to inform about some frictions in the economy. We contribute to this literature by showing the usefulness of these transitory productivity shocks in the context of trade.

The growing literature on the economic impacts of climate change and potential mitigation and adaptation mechanisms is also relevant to our study. ? analyzes agricultural adaptation to climate change on a global scale using an earlier version of the GAEZ data. ? documents significant declines in global economic activity following a temperature shock. ? incorporates a migration model to evaluate the impacts of climate change, utilizing damage assessments from natural events like storms and heatwaves. ? estimates productivity and amenity losses due to rising temperatures, predicting welfare costs of up to 20% in Africa and Latin America. Our approach complements this literature by focusing on the intra-national level in Brazil, highlighting the role of food goods' tradability.

Our paper also examines the distributional effects of productivity changes. ? measures unequal gains from trade based on variations in expenditure shares across the income distribution. The first-order approach employed in their study is also used in the counterfactual analysis by ?. ? develops a methodology for counterfactual analysis in trade models based on this first-order approach. We extend the discussion in ? by focusing on the the heterogeneity of the expenditure shares and good (or type of) specific trade frictions at the intranational.

Outline. The remainder of the paper is organized as follows. Section 2 presents the trade component of the model. Section 3 derives a welfare change formula to highlight key elements for the counterfactual exercises. Section 4 introduces a perturbation to recover missing trade shares. Section 5 develops the demand side, specifying preferences and parameter calibration. Section 6 presents results from the counterfactuals, including the policy scenario on road infrastructure. Section 7 discuss limitations and potential extensions. The final section summarizes the findings.

2 Model

We develop a spatial model of food production and trade, incorporating heterogeneity along four dimensions: the tradability of different types of food, the productivity of each location for each food type, the degree of connectedness between locations, and income heterogeneity within each location.

The model includes three productive sectors: one referred to as the outside good sector, and two sectors producing different types of food, distinguished primarily by their degree of tradability. We classify the food sectors into two groups: one facing low trade costs and the other facing high trade costs. Each location is endowed with a distribution of potential productivities for goods of each type of food, and the outside good. Within each location, a population of households resides and supplies labor inelastically. These households do not migrate, and differ in their effective labor hours, generating income heterogeneity within each location.

Our approach proceeds as follows. First, we present the model without considering any shocks — either transitory shocks from weather or "permanent" shocks from climate change. As we develop the theoretical framework, we identify key missing data necessary for estimating the model, most notably detailed information on trade flows. We then introduce a transitory weather shock into the model and derive the link between price movements and the realization of these transitory shocks. This relationship is used to estimate trade frictions and recover trade shares. Finally, we discuss the sources of exogenous variation that underpin the counterfactual analysis.

2.1 The Trade Block

Our environment is static and there is no storage technology available. There are L locations, indexed by ℓ in the set $\mathcal{L} \equiv \{1, 2, \ldots, L\}$. A mass of households Λ_ℓ lives in location ℓ. Locations are endowed with productivity parameters, described momentarily.

Sectors, Goods, and Market Structure. There are three sectors: one producing an outside good, indexed by o, and sectors producing two types of food goods. One type faces low trade costs between regions, denoted by c, and another faces high trade costs, denoted by q. One might fix ideas by thinking of goods of type c as easily traded commodities, such as rice, soybean, corn, and wheat, and think of goods indexed q as harder to trade or more perishables, such as tomatoes and lettuce. We denote $x \in \mathcal{X} \equiv \{c, q\}$ to ease the notation later. For each food type x, there is a unitary mass of goods, each indexed by $\omega \in [0, 1]$. We call a variety a pair of type and good (x, ω). In all that follows, we assume all markets are perfectly competitive so that prices are pinned down by the marginal production costs, on top of any transportation costs.

Transportation Costs. We model trade frictions as iceberg costs, and let the outside good o be traded without friction. As a result, the price of the outside good is the same across locations and, therefore, is well suited to serve as the numeraire.

For food products, all varieties of a given type x face a trade cost $\tau^x_{j,\ell}$ for the location pairs (j, ℓ) and the good type $x \in \{c, q\}$. As usual, the interpretation of $\tau^x_{j,\ell}$ is that a sourcing location ℓ needs ship $\tau^x_{j,\ell}$ units of a variety (x, ω) so that the location j receives one unit.

We normalize $\tau^x_{\ell,\ell} = 1$ for all locations ℓ and types x. Whenever $j \neq \ell$, we require that $\tau^x_{j,\ell} \geq 1$. We further require that the triangle inequality be satisfied: for any triplet of locations (j, k, ℓ), the following $\tau^x_{j,\ell} \leqslant \tau^x_{j,k}\tau^x_{k,\ell}$, so that there is no arbitrage opportunities in moving the goods around.

Variety Aggregation. Varieties are aggregated by type x with a CES function[5]. For each type of food, there is a unitary mass of varieties, which we denote by ω:

$$c^c_\ell = \left(\int_0^1 c^c_\ell(\omega)^{\frac{\nu^c-1}{\nu^c}} d\omega\right)^{\frac{\nu^c}{\nu^c-1}} \quad \text{and} \quad c^q_\ell = \left(\int_0^1 c^q_\ell(\omega)^{\frac{\nu^q-1}{\nu^q}} d\omega\right)^{\frac{\nu^q}{\nu^q-1}} \tag{1}$$

[5]One alternative interpretation is that in each location there is a mass of competitive grocery shops that aggregate all varieties (x, ω) of each type x into a composite that the households buy by means of a CES production function.

where $c_\ell^x(\omega)$ denotes the consumption of variety (x,ω) in location ℓ. The CES structure delivers the ideal price indexes for each type of food as follows:

$$P_\ell^c = \left(\int_0^1 p_\ell^c(\omega)^{1-\nu^c} d\omega\right)^{\frac{1}{1-\nu^c}} \quad \text{and} \quad P_\ell^q = \left(\int_0^1 p_\ell^q(\omega)^{1-\nu^q} d\omega\right)^{\frac{1}{1-\nu^q}} \tag{2}$$

Our trade structure can be solved independently from the preference block, provided that this CES structure is imposed. Hence, we proceed with a general formulation and later specialize on the outer utility function.

Production. There is a single production factor, labor. Production is linear in labor in all sectors. The productivity on the outside good sector at location $\ell \in \mathcal{L}$ is given by Z_ℓ^o, so its inverse denotes the input requirement to produce a unit of output:

$$Y_\ell^o = Z_\ell^o N_\ell^o \tag{3}$$

where N_ℓ^o is the amount of labor allocated to such production. Letting w_ℓ denote the wage rate prevailing at the location ℓ. The cost of producing one unity of the outside good is given

$$\frac{w_\ell}{Z_\ell^o} \tag{4}$$

For the food goods, we model their production following ? model. We denote by $Z_\ell^x(\omega)$ the efficiency of location ℓ in producing the variety ω of food type $x \in \{c, q\}$. The production technology takes the form of

$$Y_\ell^x(\omega) = Z_\ell^x(\omega) N_\ell^x(\omega) \tag{5}$$

so that the cost per unit for producing good variety (x,ω) at location ℓ is given by

$$\frac{w_\ell}{Z_\ell^x(\omega)} \tag{6}$$

Good sourcing. Consider the problem of a family living in location $j \in \mathcal{L}$ deciding where to source from. The cost in location $j \neq \ell \in \mathcal{L}$ to acquire a variety (x,ω) from location ℓ takes into account the production cost in location ℓ and the transportation costs from ℓ to location j, that is:

$$p^x_{j,\ell}(\omega) \equiv \left(\frac{w_\ell}{Z^x_\ell(\omega)}\right)\tau^x_{j,\ell} \tag{7}$$

Under the working assumption of perfect competition, location j buys from location ℓ if ℓ is able to supply at the lowest delivery cost, taking into account both production and transportation costs. The price that location j pays for the variety (x, ω) is the lowest among all potential sourcing locations:

$$p^x_j(\omega) \equiv \min\left\{p^x_{j,\ell}(\omega) : \ell \in \mathcal{L}\right\} \tag{8}$$

Food Production Technology. We assume that the productivity draws follows the structure of ?. We denote by $Z^x_\ell(\omega)$ the productivity of variety (x, ω) at location ℓ, which we refer to as "EK term" below.

For each type of good-variety pair (x, ω), a location receives a productivity draw from a location-specific Fréchet probability distribution with the cumulative distribution function:

$$F^x_\ell(\tilde{z}) = e^{-T^x_\ell \tilde{z}^{-\theta^x}}. \tag{9}$$

The draws are independent across varieties (x, ω) within and across locations. The parameter T^x_ℓ, or "State of Technology," defines the mean productivity and reflects the absolute advantage of location ℓ for type x ?. The parameter θ^x, uniform across locations, governs the dispersion of productivity draws, with higher values implying narrower comparative advantages. As in ?, θ^x represents the trade elasticity.

Price Determination. Below, we state the main results of the model and refer to a complete derivation in appendix ??. As in ?, location j faces a probability distribution of prices of a variety

$$G^x_{j,\ell}(p) = 1 - e^{-[T^x_\ell (w_\ell \tau^x_{j,\ell})^{-\theta^x}]p^{\theta^x}} \tag{10}$$

Because the productivity draws are i.i.d, this probability is the same for every variety (x, ω). This term gives the probability of location j being supplied by location ℓ with the price up to p for type x. Since location j buys from the lowest cost supplier, we next show the probability location j buy type-variety pair (x,ω) of a price of at most p. This requires that there is at least one location that supplies at the price not higher than p, as follows

$$G_j^x(p) = 1 - \prod_{\ell\in\mathcal{L}}[1 - G_{j,\ell}^x(p)] \tag{11}$$

Plugging equation (10) into (11), we recover

$$G_j^x(p) = 1 - e^{-\Phi_j^x p^{\theta^x}} \tag{12}$$

where

$$\Phi_j^x \equiv \sum_{\ell\in\mathcal{L}} T_\ell^x (w_\ell \tau_{j,\ell}^x)^{-\theta^x} \tag{13}$$

The term Φ_j^x shows how the State of Technology, T_ℓ^x, the input cost of production w_ℓ, and the trading frictions $\tau_{j,\ell}^x$ between each location ℓ and j ultimately shape the price distribution faced at the location j.

Price of Basket. As we shall see next, the state of these three forces across all locations and their interaction describes the price level in each location $j \in \mathcal{L}$. Equation (12) allows us to recover the ideal price indexes for each good type, in equation (2) , as follows:

$$P_j^x = \left(\sum_{\ell\in\mathcal{L}} T_\ell^x (w_\ell \tau_{j,\ell}^x)^{-\theta^x}\right)^{-\frac{1}{\theta^x}} \gamma^x \quad \text{for} \tag{14}$$

where γ^x is a time-invariant constant[6].

Trade Shares. We need to find out how trade flows are pinned down with given prices. To achieve that goal, let us start by computing the probability location j buys a given variety to location supplied by location $l \in \mathcal{L}$. Because the productivity draws are iid, and since there is a continuum of goods for each type, this probability turns out to be the share of goods that $\ell \in \mathcal{L}$ supply to $j \in \mathcal{L}$.

[6]This constant is equal to $\Gamma\left(\frac{\theta^x+1-\nu^x}{\theta^x}\right)^{\frac{1}{1-\nu^x}}$. $\Gamma(u)$ is the Gamma function, given by $\int_0^\infty x^{u-1}e^{-x}dx$, for $u > 0$. As we show later, once we apply logs and take differences, this constant disappears entirely

We denote by $\pi^x_{j,\ell}$ the fraction of goods of type x that location $j \in \mathcal{L}$ buys from location $\ell \in \mathcal{L}$, which is given by

$$\pi^x_{j,\ell} = \frac{T^x_\ell \left(w_\ell \tau^x_{j,\ell}\right)^{-\theta^x}}{\Phi^x_j} \equiv \frac{T^x_\ell \left(w_\ell \tau^x_{j,\ell}\right)^{-\theta^x}}{\sum\limits_{\ell \in \mathcal{L}} T^x_\ell (w_\ell \tau^x_{j,\ell})^{-\theta^x}} \tag{15}$$

In order to find out the total cost of these expenditures, we need to calculate the price of the goods that location j bought from location ℓ. Due to the Fréchet distribution for the productivity draws, the distribution of paid prices faced by location $j \in \mathcal{L}$ of varieties coming from $\ell \in \mathcal{L}$ conditional on ℓ being the cheapest supplier turns out to be equal to the distribution of prices coming from $\ell \in \mathcal{L}$ to $j \in \mathcal{L}$, that is

$$\Pr\left\{ p^x_{j,\ell}(\omega) \leq \tilde{p} \mid p^x_{j,\ell}(\omega) \leq \min_{k \in \mathcal{L}_{-\ell}} p^x_{j,k}(\omega) \right\} = G^x_j(\tilde{p}) \tag{16}$$

The result in (16) implies that the share of expenditures on type x in the location j that is supplied by location ℓ is also given by $\pi^x_{j,\ell}$.

3 Equivalent Variation

In what follows, we borrow insights from the standard demand theory, in the spirit of ? to shed light on why the separation between the trade and the demand blocks we propose is particularly useful. In particular, as we show next, because of free mobility of labor across sectors, and because the changes in productivity affect only the agricultural sector, by assumption, income in terms of the outside good is constant. Hence, changes in utility from the productivity in the food sector come from the changes the relative price of food alone.

3.1 Climate change through the lens of the Model

The average potential productivity of the food-producing sectors is defined to be $\mu^x_\ell \equiv \mathbb{E}[Z^x_\ell(\omega)]$. Because the draws for each $\omega \in [0, 1]$ comes from a Frechét distribution, this average productivity relates to T_ℓ^x according to the formula

$$T_\ell^x = \left[\mu_\ell^x\right]^{\theta^x} \kappa^x \tag{17}$$

where κ^x is a time-invariant constant common to all locations[7]. In what follows, we will assume that climate change affects T_ℓ^x, by looking at μ_ℓ^x, which we can read from the GAEZ dataset.

Let $\mathcal{V}_{i,j} \equiv V(P_j^c, P_j^q, y_i)$ be the indirect utility of an individual with income y_i in a location j, where prices are P_j^c and P_j^q. Notice that because the outside good is the numeraire, its prices do not appear in the indirect utility. Taking the log of $\mathcal{V}_{i,j}$ and its total derivative with respect to log prices and log income, we have:

$$\widehat{\mathcal{V}}_{i,j} = \sum_{x \in \mathcal{X}} \frac{\partial \log(\mathcal{V}_{i,j})}{\partial \log P_j^x} \widehat{P}_j^x + \frac{\partial \log(\mathcal{V}_{i,j})}{\partial \log y_i} \widehat{y}_i \tag{18}$$

where we use the convention $\hat{z} \equiv d\log(z)$ representing the log change in a variable z. Let $\mathrm{EV}_{i,j}$ be the equivalent variation associated with the prices changes as the proportional change in income, at pre-shock prices, which would generate the same change in utility as the total derivative above:

$$\widehat{\mathcal{V}}_{i,j} = \frac{\partial \log(\mathcal{V}_{i,j})}{\partial \log y_i} \mathrm{EV}_{i,j} \tag{19}$$

Here, $\mathrm{EV}_{i,j}$ is the variation in income that would be necessary to achieve the same variation in utility that would have happened from the variation in prices and income above, that is $\widehat{\mathcal{V}}_{i,j}$.

We recover the following formula for the Equivalent Variation using Roy's Identity, while noticing that $\hat{y}_i = 0$ since in our setting, due to the free mobility of labor across sectors and the assumption that Z_ℓ^o is not affected by Climate Change, income is constant[8]:

$$\mathrm{EV}_{i,j} = \sum_{x \in \mathcal{X}} -\mathrm{s}_{i,j}^x \widehat{P}_j^x \tag{20}$$

[7]This constant is equal to $\Gamma\left(\frac{\theta^x - 1}{\theta^x}\right)^{-\theta^x}$. $\Gamma(u)$ is the Gamma function, given by $\int_0^\infty x^{u-1} e^{-x} dx$, for $u > 0$.

[8]It is straightforward to relax this assumption.

where $s^x_{i,j}$ is the expenditure share on good x with income i at location j, at the pre-shock prices. The interpretation of $\text{EV}_{i,j}$ is the consumer's willingness to pay to avoid the price changes.

The prices changes $\widehat{P}^x_j$ for each x happen due to changes in the productivity in each crop, in each location. Through the lens of our model, we map climate change into a change in the parameter μ^x_ℓ, implemented as a change the parameter T^x_ℓ, per equation (17). In particular, we have

$$\widehat{P}^x_j = \sum_{\ell \in \mathcal{L}} \frac{\partial \log(P^x_j)}{\partial \log(\mu^x_\ell)} \widehat{\mu}^x_\ell \tag{21}$$

Using (14), (17), and (15) we have

$$\frac{\partial \log(P^x_j)}{\partial \log(\mu^x_\ell)} = -\pi^x_{j,\ell} \tag{22}$$

So that the change in the price of basket of type x in location j relates to changes in the average productivity in location ℓ according to the trade share, $\pi^x_{j,\ell}$. Using this result in (20), we recover

$$\text{EV}_{i,j} = \sum_{x \in \mathcal{X}} \text{s}^x_{i,j} \sum_{\ell \in \mathcal{L}} \pi^x_{j,\ell} \widehat{\mu}^x_\ell \tag{23}$$

Equation (23) shows that the equivalent variation depends on the components. First, it depends on the expenditure share on type x under income i and location j , $s^x_{i,j}$. This information is recoverable from the data, by means of exploit the latest consumer expenditure survey, provided a classification for what should be in each basket x. The second component is the trade-share between location j and all other suppliers locations ℓ, given the the type x, which is $\pi^x_{j,\ell}$. This component is not observed directly in the intra-national data, and one needs to estimate it. Finally, the last component is the proportional change in the average potential productivity, $\widehat{\mu}^x_\ell$.

Next, we show how we perturb the model in order to recover the estimate for $\pi^x_{j,\ell}$. The key idea is to introduce a transitory weather shock that is observed in the data and can be useful to backout these estimates, provided the structure of the model and the available data.

4 Recovering the Trade Frictions

Our main goal in this section is to estimate the trade shares, which are not directly observed in the data. In order to do so, we introduce a transitory component to agriculture productivity that depends on the realization of a weather shock.

Weather Shocks. At each period, a weather shock realizes, which we denote by ⊠ $\equiv \{h_\ell\}_{\ell \in \mathcal{L}}$, where a location ℓ receives h_ℓ. As we explain below, these weather shocks affect the productivity of food-producing sectors, affecting their production costs. For simplicity, we assume that these heat shocks do not affect the productivity of the outside sector. In what follows, we suppress h_ℓ from the notation to limit notation clutter.

In this perturbed environment, there are two terms that define the productivity of the food-producing sectors. The first is a permanent productivity that follows the structure of ?, while the second term captures the transitory effects of heat in the productivity of crops.

We denote by $\tilde{Z}^x_\ell(\omega)$ the permanent productivity of variety (x, ω) at location ℓ, which we refer to as "EK term" above. The second term accounts for how the weather realizations affect productivity temporarily, and we denote it by $G^x(h_\ell)$. We emphasize that the first term is time-invariant and the second is stochastic. The "effective efficiency" $Z^x_\ell(\omega)$ is then

$$Z^x_\ell(\omega) = \underbrace{\tilde{Z}^x_\ell(\omega)}_{\text{EK term}} \times \underbrace{G^x(h_\ell)}_{\text{Weather Shock}} \tag{24}$$

Different realizations of the weather variable h_ℓ map into different levels of "effective productivity". These effects are invariant to the location — there is no subscript ℓ in the function $G^x(\cdot)$— but we allow food types to have different sensitivities to heat. The unitary cost of production variety (x, ω) is given by

$$\tilde{w}^x_\ell \equiv \frac{w_\ell}{G^x(h_\ell)} \tag{25}$$

From the expressions above for the prices and trade shares, Equations (14) and (15), the key change is the replacement of w_ℓ by $\tilde{w}^x_\ell$:

$$P_j^x = \left(\sum_{\ell \in \mathcal{L}} T_\ell^x (\tilde{w}_\ell^x \tau_{j,\ell}^x)^{-\theta^x} \right)^{-\frac{1}{\theta^x}} \gamma^x \quad \text{and} \qquad \pi_{j,\ell}^x = \frac{T_\ell^x \left(\tilde{w}_\ell^x \tau_{j,\ell}^x \right)^{-\theta^x}}{\sum_{\ell \in \mathcal{L}} T_\ell^x (\tilde{w}_\ell^x \tau_{j,\ell}^x)^{-\theta^x}} \tag{26}$$

The log linearity of the price of the basket and the trade shares allows us to derive link between the incidence of heat and changes in prices. We exploit this link to recover estimates of these trade frictions.

4.1 From Heat Shocks to Prices Changes

In this section, we show how we recover estimates of trade costs for each type of food good. First, we develop the results that we need in order to run the structural regression.

For a type x of food, the model implies a close relationship between logarithmic changes in price and the occurrence of heat in every location. In the model, heat reduces the productivity of each sector, effectively increasing the unitary cost of production: more labor is required to produce one unit of output. Then, because the locations trade among themselves, the higher production cost in one location translates into higher bundle cost in all other locations, with the relative importance given by the trade shares. Next, we formalize this intuition.

Consider a location j of interest and a location ℓ that receives a heat shock. The price at the location j increases with an increase in the cost of production at the location ℓ according to

$$\frac{\partial \log(P_j^x)}{\partial \log(\tilde{w}_\ell^x)} = \pi_{j,\ell}^x \tag{27}$$

Equation (27) shows that the elasticity of the price index at j with respect to production costs at location ℓ is given by the expenditure share of location j from location ℓ. Intuitively, location j is more exposed to shocks at ℓ with the higher importance of ℓ as a supplier. This production cost increases with the realization of heat. By our formulation, this implies

$$\frac{\partial \log(\tilde{w}_\ell^x)}{\partial h_\ell} = -\frac{\partial \log(G^x(h_\ell))}{\partial h_\ell} \equiv \eta^x \tag{28}$$

This delivers a single semi-elasticity that is one output of our estimation procedure. Notice that we assume, for simplicity, that η^x is homogeneous between locations. This is an identification assumption. Putting all together, we recover

$$\begin{aligned} \frac{\partial \log(P_j^x)}{\partial h_\ell} &\equiv \frac{\partial \log(P_j^x)}{\partial \log(\tilde{w}_\ell^x)} \frac{\partial \log(\tilde{w}_\ell^x)}{\partial h_\ell} \\ &= \pi_{j,\ell}^x \times \eta^x \end{aligned} \tag{29}$$

The logarithm increase in the cost of a basket x in a location j goes up with a shock realized at location ℓ with two components. The first is how much location j is exposed to shocks in ℓ through trade, $\pi_{j,\ell}^x$ multiplied by how much the production cost in ℓ increases upon the realization of heat, at the margin.

This gives the price change up to a first-order approximation, with "one unit" of the h_ℓ. In reality, shocks would affect each region. To take all this into account, we take the total derivative of the price with respect to heat shocks in each location and sum it across all locations.

$$\Delta \log(P_j^x) \approx \eta^x \sum_{\ell=1}^{L} \pi_{j,\ell}^x \Delta h_\ell \tag{30}$$

In our approach is then to use variation from observed price changes and heat shock realizations to infer the trade shares $\pi_{j,\ell}^x$. The key idea is to use the structure of these trade shares in the model, together with observables in the data to recover the trade costs, allowing us to retrieve the missing shares. Toward this goal, we next describe the data we use.

4.2 Weather Data

Our weather satellite data is extracted from ? for the 1950-2021 period. We use the hourly average land temperature at the raster level of 0.1° by 0.1°[9]. We calculate the number of days of exposure to temperatures above 30°C/86°F at the quarterly level. We convert the raster-level exposure data to the municipal level by computing the municipal average exposure over the rasters contained in the municipal boundary. Ultimately, we calculate

[9]Equivalent to 11 by 11kms, or 6.5 by 6.5 miles. Owing to the curvature of the earth, the area covered in the grids increases as we approach the equator line.

the weighted state-level average of exposure, weighting municipalities by the average annual value of municipal crop production from 1999 to 2021. The crop production data comes from the Systematic Survey of Agricultural Production collected by IBGE, which we describe in more detail in the Appendix ??.

We choose 30°C as our temperature threshold, given the adverse effects that temperatures above this threshold have on crop yields, as well documented in ?. They find non-linear effects of exposure to high temperatures on maize, cotton, and soybean yields. We validate this choice for the temperature threshold. As documenting the link between heat exposure and crop yields is not entirely novel in the literature, we include them in the Appendix ??. Our analysis shows a contraction in crop yields after exposure to temperatures above $30^{\circ}C$ in the crop growing season. The estimates are statistically significant and economically relevant. After controlling for state-year factors, the semi-elasticity is around -0.4% for rice, -0.6% for soybeans, and 0.6% for beans.

4.3 Consumer Price Index Data

We use data from the official Consumer Price Index (CPI) in Brazil, taken from IBGE[10]. The most detailed data are available at the "sub-item" level (e.g., banana, bus fare, t-shirt) at the monthly frequency, which aggregates into baskets called "items" (e.g., fruits, public transportation, youths apparel), and further aggregates named "groups"(e.g., food and beverages, transportation, apparel). Nationwide, IBGE tracks a basket of sub-item prices, mimicking the average consumption basket of a family with income ranging from 1 to 40 minimum wages and living in urban areas[11].

The raw microdata consists of a panel of locations and price changes at sub-item, item, and group levels, together with the monthly weights. Our sample starts in August 1999, a date that we chose given the history of hyperinflation before 1994 and the pegged exchange rate from mid-1994 until early 1999. The last observation date is December 2023. The panel is unbalanced, with 11 locations at the beginning of the sample and 16 at the end of the

[10] In Portuguese, it is the IPCA — Índice de Preços ao Consumidor Amplo.

[11] This income range covers around 90% of the families in the latest Consumer Expenditure Survey, from 2017-2018. The national minimum wage in 2018 was R$ 954. The average commercial exchange rate against the U.S. dollar fr 2018 was approximately R$ 3,65 per US$, so the minimum wage was approximately US$ 260 in 2018.