Climate Change, Comparative Advantages, and Structural Transformation in Agriculture

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Abstract

Climate change is expected to reshape agricultural productivity and comparative advantages across countries, with important consequences for economic welfare. Yet these consequences depend not only on where productivity changes, but also on how countries consume, produce, and trade. This paper investigates how consumption patterns and international trade shape the unequal welfare consequences of climate change. I combine rich, spatially disaggregated data on crop-specific agricultural productivity under alternative climate conditions with bilateral trade flows and country-level expenditure data in a multi-country Ricardian general equilibrium trade model with non-homothetic preferences. I find that climate-induced productivity shocks reduce global welfare by 0.72% of world GDP, with particularly large losses in lower-middle-income economies. A welfare decomposition reveals that the price effect dominates the structural change effect, which captures income-driven adjustments in consumption expenditure shares. Counterfactual simulations further show that differences in food expenditure shares amplify welfare losses in poorer economies. Finally, export restrictions by major agricultural suppliers exacerbate these losses, while removing existing export taxes can partially mitigate them. These findings highlight how consumption exposure and international trade policies shape the unequal economic consequences of climate change.

JEL Classification: F13, F18, F40, Q11, Q17, Q54

Keywords: International Trade, Welfare, Trade and Environment, Agricultural Commodities, Farming, Climate Change.

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1. Introduction

Climate change has the ability to increase average temperatures and the frequency of climate extremes (Leonard et al., 2014; AghaKouchak et al., 2014, 2020). The predictions of the Intergovernmental Panel on Climate Change (IPCC) warn against a worsening of the situation in the coming years. This result in an increase in the frequency, intensity, spatial extent, and duration of extreme and increasingly complex climatic events (Bathke et al., 2015; Tavakol et al., 2020) in all regions in the world. The impact of climate change on agriculture is particularly pronounced, showing substantial disparities in various geographical areas. Food security is affected by uncertainty over domestic production and production in foreign countries. The resilience of agri-food supply chains to climate change is also of great concern.

Due to its heterogeneous impacts, climate change affects the competitivity of firms and countries' comparative advantage inducing changes in specializations between countries and adjustments in trade flows (Costinot et al., 2016; Nath, 2020, 2025). As comparative advantages evolve over time (Gaigné and Gouel, 2022), climate change and shifting patterns of specialization are likely to have significant implications for welfare and consumption baskets. A key insight is that the effects of climate change will differ across regions (Costinot et al., 2016; Rosenzweig and Parry, 1994). If climate change impacts all crops and countries uniformly, the resulting reduction in cross-country productivity differences may weaken trade incentives, leading to substantial welfare losses (Reilly and Hohmann, 1993; Randhir and Hertel, 2000). By contrast, if climate change increases productivity disparities across regions, it could amplify trade opportunities and, in doing so, help mitigate some of the welfare losses (Gouel and Laborde, 2021; Nath, 2025; Lamonaca et al., 2024).

This paper addresses these challenges by examining the macro-level consequences of climate change. My main contribution to the existing literature is threefold. First, I develop a Ricardian trade model with non-homothetic CES preferences to quantify how income effects shape the welfare consequences of climate change. The existing literature has largely relied on homothetic or quasi-linear preferences (Costinot et al., 2016; Gouel and Laborde, 2021), which suppress the feedback between income losses and food expenditure shares. The assumption of homothetic is innocuous when productivity shocks are small and symmetric. However, it becomes difficult to sustain in the context of climate change, which disproportionately lowers agricultural productivity, and therefore real income, in countries where households already devote a large share of their budget to food (Uy et al., 2013; Herrendorf et al., 2014). By allowing expenditure shares to respond endogenously to income, the model captures an amplification mechanism that is absent from prior frameworks: climate-induced income losses raise food expenditure shares, which in turn magnify the welfare losses associated with rising food prices. This single channel explains a seventeen-fold difference in the estimated welfare losses, increasing them from 0.26% to 4.6%, and yields a strongly regressive pattern of climate shocks across countries that homothetic frameworks fails to capture.

Second, I implement this framework by adapting the non-homothetic CES demand system of Comin et al. (2021) to an open-economy setting with multiple agricultural goods and intermediate inputs. This choice of preferences is disciplined by three requirements that alternative specifications fail to jointly satisfy. (*i*) The system accommodates good-specific income elasticities, thereby allowing agricultural and non-agricultural goods to exhibit empirically distinct Engel curves; (*ii*) it preserves a constant elasticity of substitution across goods, which ensures tractability in general equilibrium; (*iii*) it delivers a closed-form expression for the consumer price index in terms of observable expenditure shares and prices, rather than unobservable utility levels, which is crucial for conducting consistent welfare comparisons within a quantitative trade model. I estimate the income elasticity of demand for agrifood products at $\varepsilon_a = 0.79$, below unity and consistent with Engel's law, and show that this departure from homotheticity is quantitatively consequential: as income falls, households in low-income countries are pushed toward greater food expenditure shares, amplifying the welfare losses induced by climate shocks.

Third, I measure welfare using a money-metric utility approach (Baqaee and Burstein, 2023; Baqaee et al., 2024; Jaravel and Lashkari, 2024) that delivers consistent comparisons of the cost of living before and after climate change when preferences are non-homothetic. The money-metric utility (McKenzie, 1957; Samuelson, 1974) translates welfare changes into monetary units by evaluating the expenditure function at a reference price vector, delivering a cardinal welfare measure that is comparable across countries. This measure is directly related to the equivalent variation [1]. In the presence of non-homothetic preferences, and I decompose the total welfare effect into a price effect, capturing the welfare loss arising from climate-induced changes in relative prices of agricultural goods; and a structural change effect reflecting shifts in the share of agricultural goods in total consumption across countries. The results show that the price effect is the dominant channel of welfare transmission, exceeding the structural change effect across all income groups and specifications. This finding complement Nath (2025) by showing that, in addition to constraints on sectoral reallocation, the welfare incidence of climate change depends critically on food price changes and income-driven expenditure shares.

I rely on a rich micro-level data, covering the entire globe, from the Global Agro-Ecological Zones (Fischer et al., 2021) project of the Food and Agricultural Organization (FAO), which combines agronomic modeling with detailed geospatial information–including soil type, elevation, and climate related variables to estimate potential yields for individual crops worldwide. Comparing yields under present and future climate scenarios makes it possible to infer changes in comparative advantage across space and time. The results indicate that climate change has uneven effects on agri-food productivity and welfare, with low- and lower-middle-income economies especially vulnerable due to their reliance on climate-sensitive sectors. Exposure to climate shocks can have substantial effects on price variation compared to structural changes in demand shares

[1] To measure the aggregate welfare consequences of climate change, I adopt the equivalent variation in the sense of Hicks (1946) as clarified by Diewert (1992): $EV = e(u^1, p^1) - e(u^1, p^0)$, which measures the income change that would be equivalent to the climate shock at post-shock prices.

for agricultural products.

This paper can be related to the recent literature evaluating the gains from trade using a large class of models delivering structural gravity equations (Gouel and Laborde (2021), Costinot et al. (2016)). Gouel and Laborde (2021) build a theoretical framework with quasi-linear preferences to investigate how international trade flows are adapting to climate change. By applying a similar approach using less restrictive assumptions, I quantify the consequences of climate change on productivity and welfare.

The remainder of the paper proceeds as follows. Section 2 reviews the related literature on climate change, comparative advantage, and welfare measurement under non-homothetic preferences. Section 3 documents some key facts that motivate the analysis: the evolving nature of comparative advantages across countries and the heterogeneous exposure to climate shocks across income levels. Section 4 develops the theoretical framework, embedding non-homothetic CES preferences into a multi-country Ricardian trade model with intermediate inputs and endogenous labor supply. Section 5 describes the data, including the FAO Global Agro-Ecological Zones dataset, bilateral trade flows, and tariff data. Section 6 presents the estimation of the structural parameters, including the income elasticity of demand for agrifood products. Section 7 reports the baseline counterfactual results and decomposes the total welfare effect into price and structural change components. Section 7.3 conducts sensitivity analysis with respect to alternative income elasticities and preference specifications. In section 8 I discuss the policy implications, with a particular focus on the role of tariff reductions in mitigating welfare losses for low-income countries. Section 9 concludes and outlines directions for future research.

2. A Brief Literature Review

Key contributions on climate change, productivity and shifting comparative advantages include Costinot et al. (2012), Costinot et al. (2016), and Gouel and Laborde (2021). This literature links climate change to trade using Ricardian models that allow for land heterogeneity, with yields drawn from a Fréchet distribution (e.g., Huang et al. (2011); Costinot et al. (2012, 2016); Heerman (2020); Heerman and Sheldon (2022); Levchenko and Zhang (2013); Simonovska and Waugh (2014a,b); Caliendo and Parro (2015)). A natural implication of this framework is that, because climate change reshapes comparative advantage heterogeneously across countries, international trade becomes a key margin of adjustment: countries whose productivity declines can source food from countries where productivity has improved, thereby cushioning the welfare impact. This adaptation channel has been explored by Cui (2020), Conte et al. (2021), Gouel and Laborde (2021), and more recently Nath (2025).

I also build on prior work that provides tools to define comparative advantage at the product level in global general equilibrium models, following Eaton and Kortum (2002) and Melitz (2003), with heterogeneous productivity across products. Allowing for intra-sector heterogeneity in pro-

ductivity has important implications for empirical analysis (Chor, 2010; Costinot et al., 2012; Caliendo and Parro, 2015; Tombe, 2015). Chor (2010) decomposes productivity into a randomly generated component and a component determined by country and industry attributes. Heerman et al. (2015) and Heerman (2020) introduce sectoral heterogeneity through product-level parameters linked to product characteristics and preferences, implying that countries producing similar varieties are more likely to compete in international markets.

A related literature studies how structural transformation reshapes specialization and trade patterns. As emphasized by Uy et al. (2013) and Herrendorf et al. (2014), economic development is associated with large reallocations of expenditure and production across agriculture, manufacturing, and services. In the agri-food context, Gaigné and Gouel (2022) show that changes in consumption patterns and comparative advantage jointly shape the evolution of agricultural trade and specialization. This connection is central for the analysis because climate shocks affect agricultural productivity while income levels determine how strongly households remain exposed to food prices.

Much of the earlier climate-trade literature, however, relies on homothetic preferences or quasi-linear utility. For instance, Gouel and Laborde (2021) build a theoretical framework with quasi-linear preferences to investigate how international trade in agriculture adapts to climate change. This assumption is useful for tractability, but it abstracts from income-driven changes in food demand. This limitation is important in this setting because climate shocks affect real income, while food expenditure shares vary systematically with income levels. Assuming homothetic preferences for agrifood products is therefore restrictive when countries differ substantially in their level of development, income distribution, and per capita income (Uy et al., 2013; Chen and Juvenal, 2016).

To address this issue, I build on recent research using non-homothetic preferences in quantitative trade and structural change models. Comin et al. (2021) introduce non-homothetic CES preferences into a multi-sector general equilibrium model and derive a tractable price index that depends on income per capita, allowing expenditure shares to shift endogenously as economies develop. This feature is essential in this setting because climate shocks alter income levels, which in turn affect the share of household expenditure devoted to food. I also draw on Lewis et al. (2022), who embed this demand structure into a quantitative trade model to study how large shifts in consumption patterns feed back into global trade flows. I adapt these tools to a two-sector, multi-country, multi-factor model with intermediate goods, and use them to trace how climate-induced productivity shocks propagate through prices, expenditure shares, trade patterns, and welfare.

This paper is closely related to Nath (2025), who studies whether sectoral reallocation from agriculture to non-agriculture can mitigate the productivity effects of climate change. Like Nath, I allow food demand to be non-homothetic. Nath shows that subsistence food needs and

high trade barriers may intensify agricultural specialization in vulnerable low-income countries, thereby limiting the scope for adaptation through sectoral reallocation. This paper takes a complementary approach by shifting the focus from the supply-side reallocation margin to the demand-side welfare channel. The distinction lies in the object of decomposition. While Nath (2025) analyzes adaptation through the lens of sectoral reallocation between agriculture and non-agriculture, I decompose welfare changes using a money-metric measure that separates the cost-of-living effect from changes in the structure of consumption. Because food expenditure shares respond endogenously to income, climate-induced increases in food prices dominate the structural-change component in this framework.

Finally, this paper contributes to the literature examining the economic impact of climate change using agro-ecological characteristics (Fezzi and Bateman, 2015; Chalise and Naranpanawa, 2016; Habtemariam et al., 2017; Hossain et al., 2019; Gebreegziabher et al., 2020; Kim, 2022; Emediegwu et al., 2022; Abeysekara et al., 2023). Gebreegziabher et al. (2020) report that climate change-induced reductions in agricultural productivity could decrease average income by approximately 20 percent, while Hossain et al. (2019) find that higher temperatures and increased rainfall can enhance income and welfare. However, these studies typically rely on partial equilibrium or reduced-form approaches that abstract from international trade linkages and treat welfare losses independently of income levels. By embedding agro-ecological productivity shocks into a general equilibrium trade model with non-homothetic preferences, this paper shows that these two omissions are quantitatively important: welfare losses are substantially larger once income-dependent food expenditure shares are accounted for, and trade serves as a key general equilibrium propagation mechanism.

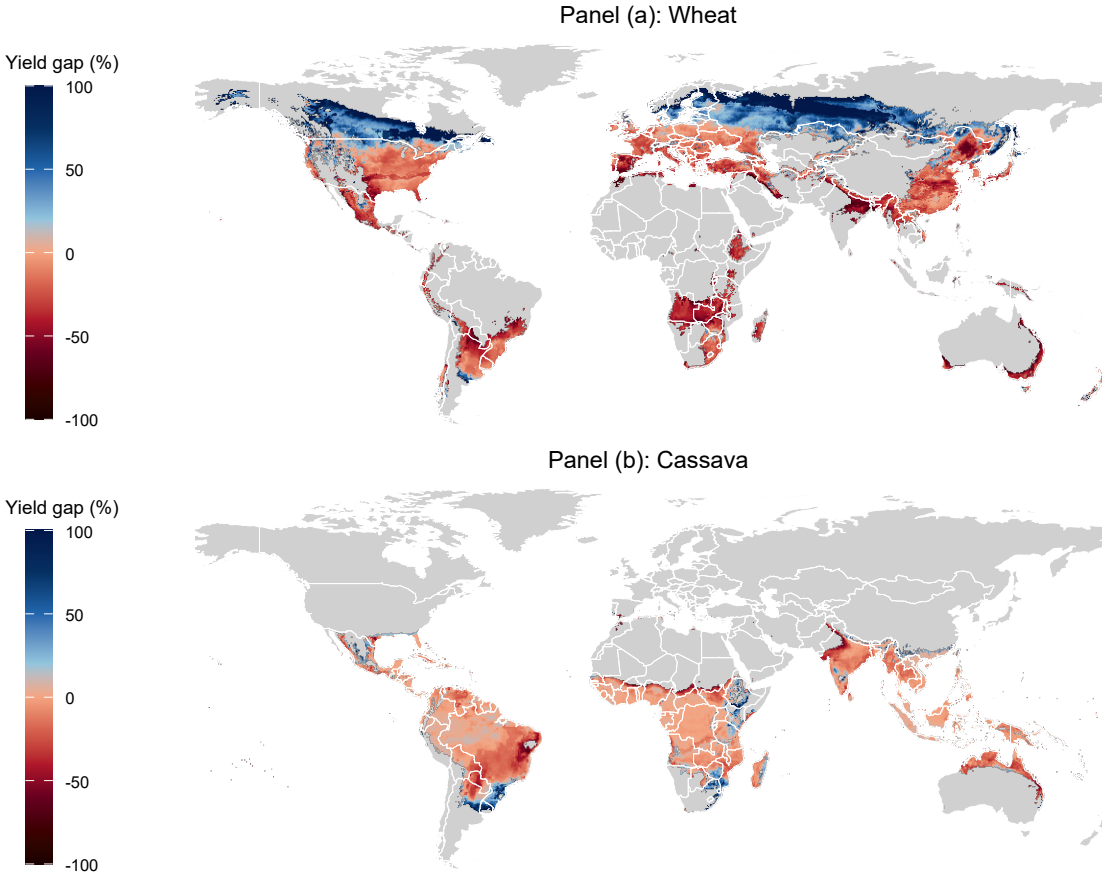
3. Stylized Facts

The analysis is based on two key insights: (*i*) the observable and evolving nature of comparative advantages across countries and (*ii*) the fact that the impact of climate change vary with consumer income levels

3.1. Evolving comparative advantages

In a globalized world, the impact of micro-level shocks is determined not only by their average magnitude but also by their spatial dispersion, especially in agriculture. If climate change affects agricultural productivity, it will, in turn, influence specialization patterns and countries' ability to benefit from trade, ultimately impacting consumer welfare. I define comparative advantages by a country's ability to specialize in producing goods for which it has relatively higher productivity or lower opportunity cost, allowing more efficient global trade (Donaldson, 2019). In line with standard Ricardian frameworks, cross-country differences in productivity are the primary drivers of comparative advantage, and these differences evolve endogenously with climate change.

Figure 1: Climate-induced changes in comparative advantage for wheat and cassava.



Notes: The figure plots, for each 5-arcminute grid cell, the percentage change in relative productivity induced by climate change, computed as the ratio of post-shock to baseline yield scaled by the corresponding world averages, minus one. Red (blue) areas indicate a deterioration (improvement) in comparative advantage relative to the world average. Grey areas correspond to cells with zero yield under the baseline scenario. Climate scenarios compare potential yields under RCP 8.5 (2041–2070) to a 1981–2010 historical baseline, assuming rain-fed cultivation at intermediate input levels. *Source:* Author's calculations using the Global Agro-Ecological Zones (GAEZ v4) database (Fischer et al., 2021), Food and Agriculture Organization (FAO).

Figure 1 documents this evolution by plotting, for each 5-arcminute grid cell, the percentage change in relative productivity induced by climate shocks. For each grid-cell, I compute the ratio of post-shock to baseline yield, scaled by the corresponding world averages, and express the result as a percentage deviation from zero. A positive (negative) value indicates that the cell gains (loses) comparative advantage relative to the world average.

Panel (a) indicates a reallocation of comparative advantage in wheat production. High-latitude economies, Canada, Russia, and Northern Europe, gain substantially in relative productivity as warmer temperatures expand viable growing areas northward. By contrast, wheat-producing regions in the Middle East, South Asia, and sub-Saharan Africa experience pronounced deterioration in their relative position, reflecting the sensitivity of wheat yields to extreme heat. Panel (b) documents a symmetric pattern for cassava, whose production is concentrated in low-income tropical economies. Across sub-Saharan Africa, South Asia, and Latin America, climate change reduces relative productivity with limited compensating gains elsewhere. These are economies where food expenditure shares are largest, making the erosion of agricultural comparative advantage particularly consequential for household welfare.

3.2. Structural Change, exposure to shocks, and income heterogeneity

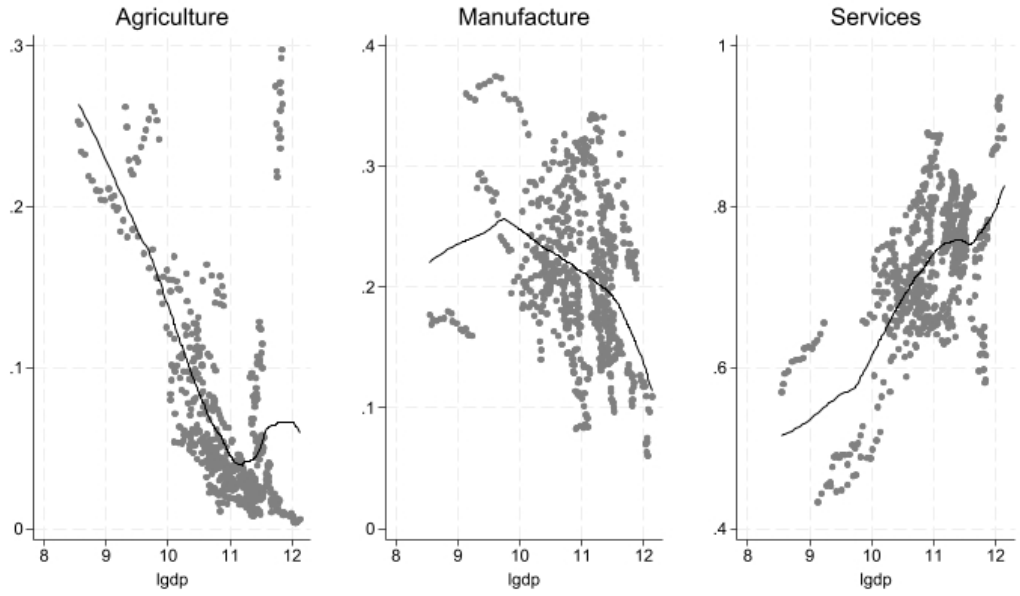
To move beyond the analysis of comparative advantage and quantify the macroeconomic consequences of climate change, this paper connects the distributional impact of climate shocks on household welfare to income levels.

In Figure 2, I illustrate sectoral value-added shares relative to GDP per capita in 43 countries from 2000 to 2014, indicating three key patterns of structural change[2]: (1) a decline in agriculture's share as economies develop, (2) a hump-shaped trajectory of industry's share, and (3) an increasing dominance of the services sector. The increase in GDP per capita is associated with a decrease in the nominal value added share in agriculture. Previous research provided extensive documentation of these trends across different sets of countries and time horizons (e.g., Buera and Kaboski (2012); Herrendorf et al. (2014)). In many low-income countries, agriculture employs a large share of the population but contributes a small share of GDP. As a result, climate shocks to agriculture are expected to reduce both labor income and food availability for a substantial portion of households. This paper explores these issues and shows that accounting for preferences exacerbates the impact of climate shocks on welfare. Poor households spend a larger share of income on food compared to wealthier households, and climate-induced increases in food prices are expected to lead to a significant decline in real purchasing power. Thus, even small GDP losses can translate into large utility losses for low-income populations.

In addition to these facts, and using the World Input-Output Database (WIOD), I measure (a)

[2] As in Buera and Kaboski (2012); Herrendorf et al. (2014), I define structural change as the reallocation of economic activity across three broad sectors (agriculture, manufacturing, and services) following the process of modern economic growth.

Figure 2: Sectoral shares in value added



Notes: The sample covers 44 countries over the period 2000–2014. Each subfigure plots a sector's share in aggregate value added (vertical axis) against log GDP per capita (horizontal axis). Value added is measured at current prices; GDP per capita is measured using expenditure-side real GDP at chained PPPs. *Source:* World Input-Output Database (WIOD).

the share of value added in gross output for each sector, and (b) the share of each sector's use of intermediate input in every other sector (including its own). Table 1 reports these shares for the five richest and five poorest countries in the sample-classified by GDP per capita—focusing on the most recent year available, 2024.

For agriculture, the results indicate a higher share of value-added in gross output for low-income countries, which implies that high-income countries use intermediate inputs more intensively than low-income countries. However, within the agricultural sector, low-income countries rely more on agricultural inputs (for e.g, seeds and animal feed), whereas high-income countries incorporate a larger share of service-based inputs. The key takeaways from this fact are: (i) the share of value added in agricultural output tends to be higher in vulnerable low-income countries than in high-income countries, and (ii) low-income countries are more exposed to micro-shocks affecting the use of inputs in agriculture.

In sum, climate shocks affects agricultural productivity unevenly across space, with the largest losses concentrated in economies where agriculture represents the largest share of output and household budgets. Although documented country-level patterns confirm that lower-income economies are more agriculture-dependent, the substantial dispersion visible within income groups suggests that aggregate data alone cannot identify which countries or crops are the most exposed. The high-resolution spatial data compiled in this paper reveal that compara-

Table 1: Input intensities for Rich and Poor Countries

	low-income countries (high-income countries)		
	Output sector		
Input Sector	**Agriculture**	**Manufacturing**	**Services**
Agriculture	0.35 (0.30)	0.12 (0.07)	0.02 (0.07)
Manufacturing	0.41 (0.33)	0.49 (0.48)	0.14 (0.27)
Services	0.24 (0.37)	0.39 (0.45)	0.84 (0.66)
Value Added Shares	0.68 (0.46)	0.32 (0.33)	0.59 (0.57)

Notes: Country groups are defined based on GDP per capita: "high-income" ("low-income") refers to the average of the 5 wealthiest (poorest) economies in the sample in term of GDP. For each output sector, intermediate input shares reflect the proportion of total intermediate expenditures allocated to each input sector. Value-added shares represent value added as a fraction of gross output for each sector. *Source:* Author's calculations based on the World Input-Output Database (WIOD).

tive advantage deteriorates most sharply in precisely those economies, where food expenditure shares are already the highest. The following sections embed these patterns into a general equilibrium Ricardian model with non-homothetic preferences to quantify how income effects shape the aggregate and distributional welfare consequences of climate change.

4. Theoretical framework

I describe a trade model in which the world consists of multiple importing countries j and exporting countries i that are endowed with land L and labor N. Similar to Eaton and Kortum (2002), I assume that countries produce and trade multiple crops indexed by $k \in \{1, ..., K\}$ and an outside good (which is a composite of manufactured goods and services). Labor can be freely allocated between crops, perfectly mobile within a country, and immobile across countries. Land consists of various fields, indexed by $f \in 1, ..., F_i$, and each field includes a continuum of diverse parcels, indexed by $\omega \in [0, 1]$. All fields in the dataset correspond to 5-arcminute grid cells as in Costinot et al. (2016). Land is allocated across crop production activities. I further assume that countries' comparative advantage is determined not only by their technological productivity (Heerman, 2020), but also by their agroecological characteristics and their trade costs. Trade flows from countries with the lowest prices (exporters) to the ones with the highest prices (importers). Following Matsuyama (2019) and Comin et al. (2021), I assume that consumers have non-homothetic preferences, such that the demand for agricultural goods varies with the level of income at given prices.

Climate change enters the model as a shock to crop productivity. This affects crop supply, producer prices, trade flows, and consumer prices. Because food demand is non-homothetic, the welfare effect of these price changes depends on income: poorer countries devote a larger share of expenditure to food and are therefore more exposed to agricultural price shocks.

4.1. Demand

I model demand through a three-stage budgeting framework. In the first stage, a representative household allocates expenditure between an agricultural aggregate C_j^a and a non-agricultural (an outside) good C_j^o. The non-agricultural good C_j^o is a homogeneous composite of manufacturing and services. It is produced under constant returns to scale using labor as the sole input, with country-specific labor productivity A_i^o, so that profit maximization implies $w_i = A_i^o$. The outside good is freely traded at zero cost and serves as the numéraire ($P^o = 1$), and all non-homotheticity in the model operates through the agricultural aggregate (Comin et al., 2021; Tombe, 2015; Matsuyama, 2019). In the second stage, expenditure on the agricultural aggregate is allocated across crops. In the third stage, expenditure on each crop is allocated across varieties from different origins. I describe each stage in turn.

Stage 1: Aggregate demand. In each country, I define a non-homothetic CES utility function for a representative agent, deriving utility from the consumption of an outside good C_j^0 and an aggregator of all crops, C_j^a. Let N_j denote population and define aggregate real consumption per capita as:

$$U_j \equiv \frac{C_j}{N_j} = \frac{E_j}{P_j N_j}, \tag{1}$$

where E_j is total expenditure and P_j is the ideal consumer price index. Following Hanoch (1975) and Comin et al. (2021), preferences are represented by a non-homothetic CES aggregator:

$$\beta_a^{1/\alpha}\, U_j^{\varepsilon_a \frac{1-\alpha}{\alpha}} \left(\frac{C_j^a}{N_j}\right)^{\frac{\alpha-1}{\alpha}} + \beta_o^{1/\alpha}\, U_j^{\varepsilon_o \frac{1-\alpha}{\alpha}} \left(\frac{C_j^o}{N_j}\right)^{\frac{\alpha-1}{\alpha}} = 1. \tag{2}$$

Here, β_a and β_o govern the relative importance of agricultural and non-agricultural goods, with $\beta_a + \beta_o = 1$. The parameter $\alpha > 0$ is the elasticity of substitution between the two goods, while ε_a and ε_o govern how the demand for each good varies with real income. The homothetic CES case is obtained when $\varepsilon_a = \varepsilon_o = 1$. When $\varepsilon_a < 1$, agricultural goods are necessities: the agricultural expenditure share declines as real consumption per capita increases, consistent with Engel's law. By contrast, when $\varepsilon_o > 1$, non-agricultural goods absorb a larger share of expenditure as income increases. This is the main departure from Costinot et al. (2016). In their model, quasi-linear preferences abstract from income effects, so food expenditure shares do not vary systematically with income. In this framework, climate-induced productivity shocks affect welfare not only through prices, trade, and comparative advantage, but also through income changes in food expenditure shares. The representative household maximizes utility subject to the budget constraint:

$$E_j = P_j^a C_j^a + P_j^o C_j^o = w_j N_j + r_j L_j + D_j, \tag{3}$$

where P_j^a and P_j^o are the prices of the agricultural composite and the non-agricultural good,

respectively. Total income is the sum of labor income, $w_j N_j$, land income, $r_j L_j$, and the trade deficit D_j, with $\sum_j D_j = 0$. Solving the household's problem (proof in the Appendix) yields the optimal expenditure share on good $b \in \{a, o\}$:

$$(\beta_b)^{\frac{1}{\alpha}} \left(\frac{C_j}{N_j}\right)^{\frac{\varepsilon_b(1-\alpha)}{\alpha}} \left(\frac{C_j^b}{N_j}\right)^{\frac{\alpha-1}{\alpha}} = \frac{P_j^b C_j^b}{E_j}. \tag{4}$$

The optimal consumption of good C_j^b can then be written as:

$$C_j^b = \beta^b N_j \left(\frac{P_j^b N_j}{E_j}\right)^{-\alpha} \left(\frac{C_j}{N_j}\right)^{\varepsilon_b(1-\alpha)}. \tag{5}$$

Defining P_j as the ideal consumer price index such that $E_j = P_j C_j$, equation (5) can equivalently be written as

$$C_j^b = \beta_b N_j \left(\frac{P_j^b}{P_j}\right)^{-\alpha} \left(\frac{C_j}{N_j}\right)^{(1-\alpha)\varepsilon_b+\alpha}.$$

Then the Engel curve for the agricultural aggregate is:

$$s_j^a \equiv \frac{P_j^a C_j^a}{P_j C_j} = \beta_a \left(\frac{P_j^a}{P_j}\right)^{1-\alpha} \left(\frac{C_j}{N_j}\right)^{(1-\alpha)(\varepsilon_a-1)}. \tag{6}$$

Equation (6) is central to the paper. When $\varepsilon_a < 1$, the agricultural expenditure share declines with real consumption per capita, consistent with Engel's law. Therefore, climate shocks that reduce real income or increase agricultural prices raise the relative importance of food in household expenditure. This is the main demand-side amplification channel in the model.

The average cost of real consumption at the country level, P_j, is given by:

$$P_j = \left[\sum_{b\in\{o,a\}} \beta_b \left(P_j^b\right)^{1-\alpha} \left(\frac{C_j}{N_j}\right)^{(\alpha-1)(\varepsilon_b-1)}\right]^{\frac{1}{1-\alpha}}. \tag{7}$$

The homothetic CES specification corresponds to the special case of equation (7) in which $\varepsilon^b = 1$ for all $b \in \{o, a\}$. As in Comin et al. (2021), P_j can also be expressed in terms of observables and demand parameters (proof in Appendix A.5).

Stage 2: Crop allocation. The agricultural aggregate is a CES aggregator:

$$C_j^a = \left[\sum_k (\beta_{jk})^{\frac{1}{\kappa}} (C_{jk})^{\frac{\kappa-1}{\kappa}}\right]^{\frac{\kappa}{\kappa-1}}, \tag{8}$$

where C_{jk} is consumption of crop k in country j, $\beta_{jk} \geq 0$ is the relative weight of crop k, and $\kappa > 0$ is the elasticity of substitution across crops. Optimal demand for each crop is:

$$C_{jk} = \beta_{jk} P_{jk}^{-\kappa} \left(P_j^a\right)^{\kappa} C_j^a, \tag{9}$$

where P_{jk} is the CES price index for crop k and $P_j^a = \left[\sum_k \beta_{jk} P_{jk}^{1-\kappa}\right]^{\frac{1}{1-\kappa}}$.

Stage 3: Variety allocation. Consumption of each crop C_{jk} depends on the consumption of varieties from different origins C_{ijk}, aggregated as:

$$C_{jk} = \left[\sum_i (\beta_{ijk})^{\frac{1}{\sigma}} (C_{ijk})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{10}$$

where σ is the substitution elasticity between varieties across all crops (Costinot et al., 2016), and $\beta_{ijk} > 0$ is the relative weight of varieties. Optimal consumption of a variety is:

$$C_{ijk} = \beta_{ijk} \; p_{ijk}^{-\sigma} \; P_{jk}^{\sigma} \; C_{jk}, \tag{11}$$

where p_{ijk} is the price of variety (i,k) in country j and $P_{jk} = \left[\sum_i \beta_{ijk} \, p_{ijk}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$.

Demand equilibrium. Combining equations (6), (9), and (11), the bilateral demand for variety (i,k) in country j can be expressed as:

$$C_{ijk} = \beta^a \left(\frac{\beta_{ijk} \, p_{ijk}^{1-\sigma}}{P_{jk}^{1-\sigma}}\right) \left(\frac{\beta_{jk} P_{jk}^{1-\kappa}}{(P_j^a)^{1-\kappa}}\right) \left(\frac{P_j^a}{P_j}\right)^{1-\alpha} \left(\frac{C_j}{N_j}\right)^{(1-\alpha)(\varepsilon_a - 1)} P_j C_j. \tag{12}$$

This expression has the same nested CES structure as in Costinot et al. (2016). The main difference is that bilateral demand varies with real income per capita, in addition to relative prices. This expression makes explicit how trade flows depend on income per capita through the non-homotheticity parameter ε_a. The substitution elasticities κ and σ are taken from the literature, while the remaining preference parameters, β^a, β_{jk}, β_{ijk}, α, ε_a, are estimated from the model.

4.2. Supply

As in Costinot et al. (2016), countries differ in their agro-ecological conditions, and within each country land is composed of heterogeneous fields. Climate change affects the supply side through crop- and field-specific productivity shocks.

Technology. The non-agricultural good is produced using labor only under constant returns to scale. Let A_i^o denote labor productivity in the non-agricultural sector. Since the outside good

is freely traded and used as the numeraire, profit maximization implies

$$w_i = A_i^o \quad , \tag{13}$$

where w_i denotes the wage. Crop production uses land and labor. Land in country i is divided into fields $f \in \mathcal{F}_i$, each with surface s_{if}. Each field contains a continuum of parcels indexed by $\omega \in [0,1]$. If parcel ω in field f is allocated to crop k, the output is given by:

$$Q_i^{fk}(\omega) = A_i^{fk}(\omega) \min \left\{ L_i^{fk}(\omega), \frac{N_i^{fk}(\omega)}{\nu_i^f(\omega)} \right\}, \tag{14}$$

where $L_i^{fk}(\omega)$ denotes the amount of land used on parcel ω, $N_i^{fk}(\omega)$ denotes labor, $A_i^{fk}(\omega)$ is parcel-level productivity, and $\nu_i^f(\omega)$ captures labor intensity. Land and labor are therefore perfect complements in crop production.

Parcel-level productivity and labor intensity are unobserved and drawn independently from Fréchet distributions with shape parameter $\theta > 1$. The scale parameters are chosen so that

$$A_i^{fk} = E\left[A_i^{fk}(\omega)\right], \qquad \nu_i = E\left[\nu_i^f(\omega)\right]. \tag{15}$$

The GAEZ data provide the average productivity of crop k in field f, A_i^{fk}. The parameter θ governs the extent of within-field heterogeneity. A lower value of θ implies greater productivity dispersion across parcels and therefore stronger comparative advantage.

Land allocation. Producers allocate each parcel to the crop that delivers the highest value of the marginal product, provided that this value exceeds the labor cost of operating the parcel. Since the wage is $w_i = A_i^o$, the country-specific labor-cost term can be summarized by

$$a_i \equiv A_i^o \nu_i. \tag{16}$$

The term a_i captures cross-country differences in agricultural labor costs, arising from differences in wages, labor requirements, or both.

For a given parcel ω, the producer compares the value of producing each crop,

$$p_i^1 A_i^{f1}(\omega), \ldots, p_i^K A_i^{fK}(\omega),$$

with the labor-cost threshold required to operate the parcel,

$$A_i^o \nu_i^f(\omega).$$

This labor-cost threshold is not crop-specific and therefore enters the allocation problem only

once. A parcel is allocated to crop k if

$$p_i^k A_i^{fk}(\omega) = \max\left\{A_i^o \nu_i^f(\omega), p_i^1 A_i^{f1}(\omega), \ldots, p_i^K A_i^{fK}(\omega)\right\}.$$

Let π_i^{fk} denote the share of field f in country i allocated to crop k. Under the Fréchet assumption, this share is

$$\pi_i^{fk} = \frac{\left(p_i^k A_i^{fk}\right)^\theta}{a_i^\theta + \sum_{\ell \in \mathcal{K}} \left(p_i^\ell A_i^{f\ell}\right)^\theta}. \tag{17}$$

Equation (17) shows that the share of land allocated to a crop increases with its producer price p_i^k and field-level productivity A_i^{fk}. By contrast, a higher a_i reduces the share of land that is profitably allocated to crop production. In the empirical implementation, θ is taken from Costinot et al. (2016), while a_i is calibrated to match initial cultivated land in each country.

Crop supply. Total output of crop k in country i is obtained by aggregating production over all fields $Q_i^k = \sum_f \int_0^1 Q_{ifk}(\omega) d\omega$. As demonstrated in Appendix A.4, aggregate supply of crop k in country i is:

$$Q_i^k = \sum_{f \in \mathcal{F}_i} s_{if} A_i^{fk} \left[\frac{\left(p_i^k A_i^{fk}\right)^\theta}{a_i^\theta + \sum_{\ell \in \mathcal{K}} \left(p_i^\ell A_i^{f\ell}\right)^\theta}\right]^{\frac{\theta-1}{\theta}}. \tag{18}$$

Equation (18) maps field-level productivity data into country-level crop supply. Climate change enters through a shift in field-crop productivity. This shock changes land allocation, crop output, producer prices, trade flows, and consumer prices.

4.3. Trade costs and market clearing.

International trade in crops is subject to iceberg trade costs $\tau_{ij}^k \geq 1$. The delivered price of crop k from country i to country j is $p_{ij}^k = \tau_{ij}^k p_i^k$. Following Eaton and Kortum (2002), the price index for crop k in country j is:

$$P_{jk} = \gamma \, \Phi_{jk}^{-1/\theta},$$

with $\gamma = [\Gamma((\theta + 1 - \sigma)/\theta)]^{1/(1-\sigma)}$ and $\Phi_{jk} = a_i^\theta + \sum_k \left(\tau_{ij}^k p_i^k A_i^{fk}\right)^\theta$. For each crop variety, market clearing requires that total production of crop k in country i equals total shipments to all destination countries, including iceberg trade costs:

$$Q_i^k = \sum_j \tau_{ij}^k C_{ij}^k. \tag{19}$$

Land allocation is defined at the field level. Each parcel is either allocated to one crop or left uncultivated:

$$\pi_i^{f0} + \sum_{k \in \mathcal{K}} \pi_i^{fk} = 1\ , \tag{20}$$

where π_i^{fk} is the share of field f allocated to crop k, and π_i^{f0} is the share of field f that is not cultivated.

Labor is mobile across sectors within a country. Labor-market clearing requires total labor to be allocated between agriculture and the non-agricultural sector:

$$N_i = N_i^o + N_i^a. \tag{21}$$

The outside good is produced using labor only and is freely traded, so the wage is pinned down by productivity in the outside sector, $w_i = A_i^o$. The labor-cost component in agriculture is summarized by the country-specific shifter $a_i = A_i^o \nu_i$, which is calibrated in the empirical implementation.

4.4. Definition of the competitive equilibrium

An equilibrium is a vector $\{C_{ij}^k,\ Q_i^k,\ p_i^k,\ p_{ij}^k,\ \pi_i^{fk},\ P_{jk}, P_j^a, P_j\}$ such that households maximize utility, producers maximize land rents, goods markets clear, and land and labor allocation conditions are satisfied. The equilibrium satisfies the demand conditions (12), (9), and (11); the supply condition (18); and the market-clearing conditions (19)–(21), given structural parameters $\{\sigma, \kappa, \alpha, \varepsilon_a, \varepsilon_o, \beta_a, \beta_o, \theta, a_i\}$ and endowments $\{L_i, N_i\}$.

The model delivers a set of equilibrium conditions that map field-level productivity shocks into changes in trade flows, prices, and household welfare. Taking the model to the data requires estimates of two sets of objects. In section 5 I describe the data sources used to discipline the model's equilibrium conditions, including bilateral trade flows, tariffs, trade costs, sectoral expenditure shares, and field-level agricultural productivity. Section 6 then details the estimation and calibration strategy for the structural parameters $\{\sigma, \kappa, \alpha, \varepsilon_a, \varepsilon_o, \beta_a, \beta_o, \theta, a_i\}$ that govern the demand system and land allocation. Together, these inputs make it possible to simulate the counterfactual equilibrium under climate change and compute the welfare decomposition in Section 7.

5. Data

5.1. Agricultural Productivity

The counterfactual analysis compares two scenarios for 2010: a baseline economy without climate-induced productivity shocks and a counterfactual economy incorporating these shocks. Productivity data come from the Global Agro-Ecological Zones project (FAO et al., 2012), a joint initiative of the Food and Agriculture Organization (FAO) and the International Institute for Applied Systems Analysis (IIASA). GAEZ data combines agronomic crop modeling with detailed geospatial information, including soil type, terrain, elevation, and climate related vari-

ables, to estimate potential yields for individual crops at a 5-arcminute resolution. The database provides yield estimates under both rain-fed and irrigated conditions, covering over 280 million grid cells worldwide.

The current version of GAEZ (v4.0) contains spatial databases covering: (*i*) naturalresource endowments relevant for agricultural use; (*ii*) assessments of land suitability and attainable yields under alternative input and management assumptions; and (*iii*) harvested area, yields, and production of major food and fiber commodities for rain-fed and irrigated land in 2010. I use GAEZ to construct two vectors of crop-level productivity at the parcel level: one under the current climate and one under a future climate scenario. The difference between these two vectors constitutes the productivity shock that I feed into the model.

5.2. Input-Output Data

The input-output structure of the economy is drawn from two complementary sources. GTAP v11 data (Aguiar et al., 2022) provides social accounting matrices and bilateral input-output tables for 141 regions and 65 sectors, from which I extract the shares of intermediate inputs used across sectors. I complement GTAP with the World Input-Output Database Timmer et al. (2015), which provides harmonized time-series input-output tables for 43 countries and 56 sectors over the period 2000–2014. WIOD is used in Section 3 to document the structural facts that motivate the framework: the evolution of sectoral value-added shares with income, and the differential intensity of intermediate input use between countries. Together, these two sources make it possible to characterize how the agricultural sector is embedded in the broader production structure across income groups.

5.3. Output, Price, and Trade Flow Data

Crop output and price are sourced from the FAOSTAT database. Bilateral trade values for agricultural products are also drawn from FAOSTAT, which aggregates them from UN COMTRADE to its own product nomenclature, ensuring consistency between trade and production data at the crop level. The value of crop final consumption is computed as the residual between production plus imports, minus exports, when positive.

Data for non-agricultural sectors (manufacturing and services), are sourced from GTAP (Aguiar et al., 2022), which provides a consistent set of social accounting matrice data. The final sample covers 50 countries and 10 crops selected on the basis of their share of global crop production value; the included countries account for 89.7% of world crop output value, while the selected crops represent 71.1% of global crop production. The full list of countries and crops is provided in Appendix A.6. Tariff data are obtained from the TRAINS database through the World Integrated Trade Solution (WITS), which provides detailed product-level information on applied tariffs. GDP per capita and income-related variables are drawn from the World Bank

Development Indicators.

6. Estimation

In this section, I describe how the model is brought to the data. The empirical implementation follows the demand and supply blocks developed in Section 4. I first construct the baseline economy using data on production, land use, bilateral trade, expenditure, income, population, and field-crop productivity. I then estimate the demand-side parameters using the non-homothetic expenditure-share equations from Section 4.1 and calibrate the supply side using the land-allocation and crop-supply equations from Section 4.2. Finally, I solve the model under baseline and counterfactual productivity conditions and compute welfare changes.

6.1. Demand-side estimation

The demand-side estimation relies on the non-homothetic equations derived in Section 4.1. In particular, I use the agricultural expenditure share in equation (6), which links the share of expenditure allocated to agriculture to relative prices and consumption per capita. For each country i, the agricultural expenditure share is

$$s_i^a = \beta_a \left(\frac{P_i^a}{P_i}\right)^{1-\alpha} \left(\frac{C_i}{N_i}\right)^{(1-\alpha)(\varepsilon_a-1)}, \tag{22}$$

in the same way that the non-agricultural expenditure share is

$$s_i^o = \beta_o \left(\frac{P_i^o}{P_i}\right)^{1-\alpha} \left(\frac{C_i}{N_i}\right)^{(1-\alpha)(\varepsilon_o-1)}. \tag{23}$$

Taking the ratio of equations (22) and (23) gives

$$\frac{s_i^a}{s_i^o} = \frac{\beta_a}{\beta_o} \left(\frac{P_i^a}{P_i^o}\right)^{1-\alpha} \left(\frac{C_i}{N_i}\right)^{(1-\alpha)(\varepsilon_a-\varepsilon_o)}. \tag{24}$$

In the baseline specification, I normalize $\varepsilon_o = 1$. The estimating equation becomes

$$\frac{s_i^a}{s_i^o} = \frac{\beta_a}{\beta_o} \left(\frac{P_i^a}{P_i^o}\right)^{1-\alpha} \left(\frac{C_i}{N_i}\right)^{(1-\alpha)(\varepsilon_a-1)}. \tag{25}$$

I estimate the upper-level demand parameters by nonlinear least squares, minimizing the squared distance between the relative expenditure share observed in the data and the relative expenditure share implied by the model:

$$\min_{\beta_a,\beta_o,\alpha,\varepsilon_a} \sum_i \left[\frac{\beta_a}{\beta_o} \left(\frac{P_i^a}{P_i^o}\right)^{1-\alpha} \left(\frac{C_i}{N_i}\right)^{(1-\alpha)(\varepsilon_a-1)} - \frac{s_i^a}{s_i^o}\right]^2, \tag{26}$$

with $\beta_a + \beta_o = 1, \quad \beta_a \geq 0, \quad \beta_o \geq 0, \quad \alpha > 0$. The relative price term and real consumption per capita are constructed from the baseline data. Since total expenditure satisfies $E_i = P_i C_i$, real consumption per capita is measured as $\frac{C_i}{N_i} = \frac{E_i}{P_i N_i}$. The estimated demand parameters $\{\beta_a, \beta_o, \alpha, \varepsilon_a\}$ are reported in Table 2.

6.2. Supply-side estimation

The supply side estimation relies on the land-allocation equation (17) and the crop-supply equation (18) of section 4.2. Following Costinot et al. (2016), parcel-level productivity and labor requirements are unobserved and drawn from Fréchet distributions with a common shape parameter θ. In the baseline calibration, I take θ from Costinot et al. (2016). The country-specific labor-cost shifter a_i, defined in equation (16), is calibrated to match observed cultivated land in each country. Specifically, for a given value of θ, the model share of field f allocated to crop k is

$$\pi_{ifk}(\theta, a_i) = \frac{\left(p_i^k A_i^{fk}\right)^\theta}{a_i^\theta + \sum_{\ell \in \mathcal{K}} \left(p_i^\ell A_i^{f\ell}\right)^\theta}. \tag{27}$$

From this share, the predicted cultivated area in country i is:

$$L_i(\theta, a_i) = \sum_{k \in \mathcal{K}} \sum_{f \in \mathcal{F}_i} s_{if} \ \pi_{ifk}(\theta, a_i). \tag{28}$$

Following Costinot et al. (2016), I estimate a_i, conditional on θ, so that the predicted cultivated area exactly matches its observed counterpart:

$$L_i(\theta, a_i) = L_i \quad \forall i. \tag{29}$$

a_i is the country-specific labor-cost shifter governs the profitability threshold for land use. A higher value raises the labor-cost threshold required to operate parcels and reduces the share of land that is profitably cultivated, consistent with equation (20). I obtain a_i from equation (30) by solving a nonlinear calibration problem:

$$\min_{a_i > 0} \left[\log L_i(a_i; \theta) - \log L_i^{\text{data}}\right]^2. \tag{30}$$

Given A_i^{fk}, a_i, θ, and producer prices p_i^k, aggregate crop supply q_i^k is computed using equation (18).

6.3. Climate counterfactuals

The counterfactual analysis compares two economies for 2010. The first is the baseline economy, constructed using observed productivity conditions. The second is a counterfactual economy in which field-crop productivity incorporates climate-induced productivity shocks. Climate shocks

enters the model through the productivity term A_i^{fk} in the land-allocation and crop-supply equations. Let A_i^{fk} denote baseline productivity and $A_i^{fk\prime}$ denote post-shock productivity. The field-crop productivity shock is defined as

$$\Delta A_i^{fk} = A_i^{fk\prime} - A_i^{fk}. \tag{31}$$

In the counterfactual equilibrium, equation (18) becomes

$$Q_i^{k\prime} = \sum_{f \in \mathcal{F}_i} s_{if} A_i^{fk\prime} \left[\frac{\left(p_i^{k\prime} A_i^{fk\prime} \right)^{\theta}}{a_i^{\theta} + \sum_{\ell \in \mathcal{K}} \left(p_i^{\ell\prime} A_i^{f\ell\prime} \right)^{\theta}} \right]^{\frac{\theta-1}{\theta}}. \tag{32}$$

All structural parameters are held fixed across the baseline and counterfactual equilibria. Thus, differences between the two equilibria are driven by the productivity shift from A_i^{fk} to $A_i^{fk\prime}$. These shocks affect land allocation, crop output, producer prices, delivered prices, bilateral trade flows, price indices, and welfare.

6.4. Welfare Measurement

To quantify the consequences of climate change, I measure household welfare using the equivalent variation (EV) in fixed final preferences (Baqaee and Burstein, 2023; Baqaee et al., 2024; Jaravel and Lashkari, 2024). The EV evaluates the income gain or loss associated with moving from the baseline to the counterfactual equilibrium, holding utility fixed at the post-shock level u:

$$\Delta W = \frac{e(P,\, u) - e(P',\, u)}{e(P,\, u)}, \tag{33}$$

where $e(\cdot)$ is the expenditure function derived from the non-homothetic CES preferences, $P = (P_j^a, P_j^o)$ denotes the vector of agricultural and non-agricultural prices at the baseline equilibrium, and $P' = (P_j^{a\prime}, P_j^{o\prime})$ denotes the corresponding prices at the counterfactual equilibrium induced by the climate productivity shock. [3] Hence, ΔW measures the proportional change in the cost of reaching the post-shock utility level u, evaluated at baseline prices P versus counterfactual prices P'. A negative value indicates a welfare loss, since the post-shock price vector requires higher expenditure to attain the same utility level. Conversely, a positive value indicates a welfare gain.

The total welfare effect can be decomposed into two components. Let $P(s, \cdot)$ denote the cost of aggregate real consumption under constant expenditure shares, $P'(s', \cdot)$ the cost under endogenous expenditure shares, and P^h the homothetic CES price index holding shares constant in the

[3] As in Comin et al. (2021), the expenditure function derived from the non-homothetic CES preferences is $e(\beta, P, u) = \left[\sum_b \beta_b (P_j^b)^{1-\alpha}\, u^{(1-\alpha)\varepsilon_b} \right]^{1/(1-\alpha)}$.

counterfactual. Then:

$$\Delta W = 1 - \underbrace{\frac{e(P'(s',\cdot),\, u)}{e(P^h,\, u)}}_{\text{structural change effect}} \times \underbrace{\frac{e(P^h,\, u)}{e(P(s,\cdot),\, u)}}_{\text{price effect}}. \tag{34}$$

The price effect captures welfare losses arising from climate-induce shocks in relative prices. The structural change effect captures the additional welfare impact operating through income-driven shifts in expenditure shares. The decomposition in equation (34) isolates these two channels and is a key object of interest.

7. Results

7.1. Parameter values

Table 2 reports the parameter values used in the simulations. The substitution elasticities κ, σ, and the heterogeneity parameter within fields θ are taken from Costinot et al. (2016). The upper-level demand parameters $\{\beta_a, \beta_o, \alpha, \varepsilon_a, \varepsilon_o\}$ that are common across countries are estimated using equation (26). The country-specific labor-cost shifter a_i is calibrated separately to match observed cultivated land using equation (30).

Table 2: Parameter estimates

Parameter	Estimate	95% CI
Upper-level demand parameters		
β_a	0.49	[0.40, 0.53]
	(0.03)	
β_o	0.51	[0.47, 0.60]
	(0.03)	
α	0.50	[0.30 , 0.60]
	(0.05)	
ε^o	1.00	—
	—	
ε^a	0.79	[0.72, 0.87]
	(0.04)	
Lower-level demand elasticities		
κ	2.82	—
σ	5.4	—
Supply side parameter		
θ	2.46	—

Notes: Author's calculation using GTAP data. Standard errors in parentheses. Upper-level demand parameters are estimated on a cross-section data for the year 2011. κ, σ, and θ are from Costinot et al. (2016).

I obtain point estimates of $\alpha = 0.5$ and $\varepsilon_a = 0.79$, reported in Table 2. Both parameters are

statistically significant and consistent with the conditions specified in Section 4.1, namely $\alpha > 0$ and $0 < \varepsilon^a < 1$. The income elasticity ε_a lies strictly below unity, implying a strong and robust departure from homotheticity in food demand.

The estimates are consistent with those reported by Comin et al. (2021), who estimate non-homothetic CES preferences using household-level data from the Consumer Expenditure Survey and obtain income elasticities below unity for agricultural goods. First, the estimated substitution elasticity $\alpha = 0.5$ implies that agricultural and non-agricultural goods are net complements in the sense of Hicks (1946): a one percent increase in the relative price of food raises the agricultural expenditure share by $(1 - \alpha) = 0.5$ percent, leaving households with less to spend on non-agricultural goods.

Second, the estimated non-homotheticity parameter $\varepsilon^a = 0.799 < 1$ implies that the consumption share of agricultural goods is diminishing in real income, consistent with Engel's law (Herrendorf et al., 2014; Matsuyama, 2019). The income elasticity of the agricultural expenditure share is $(1-\alpha)(\varepsilon^a - 1) = -0.100$: a one percent increase in real consumption per capita reduces the agricultural expenditure share s^a by approximately 0.10 percent, holding prices constant. This income effect is a central amplification mechanism in the model: climate-induced reductions in real income push food expenditure shares upward and amplify the welfare burden on households that already devote a large share of their budget to food.

Finally, I assess the robustness of the demand estimates to the calibrated value of α. Appendix A.7 reports the income elasticity ε^a for $\alpha \in [0.3, 0.8]$. Across this range, ε^a vary between 0.499 and 0.857. The amplification mechanism at the core of the welfare results therefore does not depend on a particular calibration of α. Regardless of the assumed degree of complementarity between food and non-food goods, higher-income households devote a smaller share of their budget to food, and climate shocks impose larger welfare burdens on lower-income economies.

7.2. Climate shocks and household welfare

Columns (4) and (5) of Table 3 report the estimated welfare changes, ΔW, for the 50 countries in the sample. According to the results, the decrease in global welfare is underestimated when income effects are not considered. Climate change induces a global welfare decrease of 4.6 %, versus a 0.26 percent decrease when income effects are ignored. The result indicates that low- and lower-middle-income countries such as Malawi, Ghana, and Sudan, experience the most severe negative effects, especially when accounting for demand-side changes in consumption patterns. The findings suggest that these economies are highly vulnerable due to their reliance on agriculture, which is more sensitive to climate shocks. In contrast, some countries, for example, Germany, Canada, United kingdom, Netherland and Russia, experience considerable benefits from climate change, reflecting their economic diversification and greater adaptive capacity. When adjusting for non-homothetic preferences—acknowledging that income influences

spending patterns—the economic losses become even more pronounced for developing countries, indicating a disproportionate burden on poorer nations.

The results presented in Table 4 highlight the disproportionate impact of climate change on welfare across income groups. Specifically, low-income countries are projected to experience an aggregate welfare loss of approximately 15.2%, followed by a 7.4% loss in lower-middle-income countries. In contrast, upper-middle-income and high-income countries face significantly smaller losses of 3.1% and 0.3%, respectively. Low-income economies are more reliant on climate-sensitive sectors such as agriculture, and have limited access to trade and technological adaptation mechanisms. As a result, climate shocks directly undermine both production and consumption in these regions, exacerbating existing vulnerabilities.

To conclude the quantitative analysis, I also investigate the role played by trade. I consider a world economy in which preferences and technology are described as in section 4, and simulate a policy change from a positive export tax to full liberalization (i.e., zero tariffs). Column (2) of Table 4 reports the result. I find that removing tariffs has a positive effect as it reduces the loss in welfare (-2.8%). Specifically, welfare losses in low-income countries decrease from -15.2% to -14.8% , and from -7.4% to -6.9% in lower-middle-income countries. Although the magnitude of the reduction is modest, it signals that trade liberalization can improve resource allocation and ease market access, allowing countries to adjust to productivity shocks induced by climate change.

7.3. Sensitivity analysis

In this section, I conduct a sensitivity analysis using the same data as in the baseline specification. I assess the stability of the results when using different income elasticities, which helps clarify how country groups respond to these shocks. I do this by varying the income elasticity of demand, which shifts a larger share of consumer spending toward agricultural goods. The table shows that as the income elasticity of demand for agricultural goods increases, aggregate welfare losses increase, particularly for low- and lower-middle-income countries. When the income elasticity of the demand for agrifood products increases, households, especially in poorer countries, allocate a larger share of income to food. Given Engel's Law and non-homothetic preferences, food become more essential in utility and more expensive, and households suffer a larger utility loss.

The findings also suggest that the welfare loss induced by climate-driven price changes exceeds the loss induced by structural changes in demand shares. The impact of climate change on relative prices plays a dominant role in explaining welfare losses. In contrast, the structural effect—which captures how climate change shifts demand shares across sectors—has a smaller impact.

Table 3: Baseline Counterfactual Results

Country	Classification		Welfare Change	
		Crop output as % of total GDP (3)	Full Adjustment (homothetic preferences) (4)	Full Adjustment non - homothetic preference (5)
Ghana	Lower-middle-income	10.72	-0.106	-0.685
Sudan	Lower-middle-income	3.89	-0.068	-0.234
Canada	High-income	0.6	0.006	0.711
Congo	Low-income	15.35	-0.107	-0.558
Malawi	Low-income	74.92	-0.491	-0.561
Venezuela	Upper-middle-income	2.5	-0.038	-0.901
Thailand	Upper-middle-income	6.05	-0.073	-0.020
Nigeria	Lower-middle-income	7.92	-0.053	-0.436
Brazil	Upper-middle-income	3.19	-0.015	-0.324
South Africa	Upper-middle-income	1.24	-0.005	-0.368
Bangladesh	Lower-middle-income	12.36	-0.082	-0.295
Cameroon	Lower-middle-income	9.38	-0.032	-0.284
Australia	High-income	0.79	-0.001	-0.517
Indonesia	Lower-middle-income	8.12	-0.025	-0.212
Pakistan	Lower-middle-income	8.51	-0.013	-0.395
Kazakhstan	Upper-middle-income	3.48	-0.008	-0.266
Tanzania	Low-income	19.56	-0.054	-0.213
Ecuador	Upper-middle-income	8.26	-0.002	-0.556
Algeria	Upper-middle-income	2.51	-0.009	-0.252
Netherlands	High-income	0.33	0.001	0.978
India	Lower-middle-income	7.41	-0.016	-0.166
Colombia	Upper-middle-income	2.36	-0.018	0.132
Burma	Lower-middle-income	49.81	-0.112	-0.166
Argentina	Upper-middle-income	4.24	0.005	-0.392
Germany	High-income	0.17	0.001	0.976
Malaysia	Upper-middle-income	4.78	-0.005	-0.062
United Kingdom	High-income	0.16	0.002	0.927
Cote d'Ivoire	Lower-middle-income	7.3	-0.028	-0.002
Mexico	Upper-middle-income	1.06	-0.004	-0.215
Vietnam	Lower-middle-income	22.5	-0.065	-0.082
Romania	Upper-middle-income	2.8	-0.005	-0.133
Korea Republic of	High-income	1.4	-0.003	-0.091
United States	High-income	0.83	-0.001	-0.216
Uganda	Low-income	33.83	-0.039	-0.150
Philippines	Lower-middle-income	5.65	-0.018	0.070
Iran	Upper-middle-income	2.46	-0.005	-0.114
Morocco	Lower-middle-income	3.27	-0.019	-0.179
Ethiopia	Low-income	11.93	-0.007	-0.140
Ukraine	Lower-middle-income	5.58	-0.002	-0.167
Japan	High-income	0.62	0.001	-0.123
France	High-income	0.33	-0.001	-0.489
Greece	High-income	1.19	-0.001	-0.204
China	Upper-middle-income	4.56	0.002	-0.037
Turkey	Upper-middle-income	2.85	0.001	-0.020
Poland	High-income	0.66	0.001	-0.952
Italy	High-income	0.38	-0.001	-0.254
Uzbekistan	Lower-middle-income	20.76	0.014	0.052
Spain	High-income	0.43	0.001	-0.695
Russia	Upper-middle-income	1.62	0.011	0.185
Egypt	Lower-middle-income	5.25	-0.004	0.865
World		1.8	-0.0025	-0.046

The implication of these results is that relative price changes matter more than sectoral reallocation. The primary welfare channel of climate change is not how much the economy restructures, but how much consumers pay for essential goods—especially in countries where food makes up a large share of consumption. Consequently, policy efforts that address price volatility and improve access to affordable food may be more effective in protecting household welfare than those focused solely on long-run structural adjustments.

Moreover, the price effect is more severe for poorer households than for richer ones. The welfare loss is not uniform and is greater in countries where food still dominates the consumption basket. These effects are consistent with findings from Hottman and Monarch (2018) and Atkin et al. (2020), who show that lower-income households tend to experience the highest price inflation, while higher-income households are least affected.

Table 4: Aggregate Welfare Loss by Income Group

Income Group	Tariff removal	Income elasticities				
		$\varepsilon_a = 0.79$	$\varepsilon_a = 0.83$	$\varepsilon_a = 0.86$	$\varepsilon_a = 0.91$	$\varepsilon_a = 0.95$
	(2)	(3)	(4)	(5)	(6)	(7)
Low	-0.148	-0.152	-0.163	-0.181	-0.211	-0.253
Lower-middle	-0.069	-0.074	-0.081	-0.092	-0.111	-0.138
Upper-middle	-0.036	-0.031	-0.033	-0.036	-0.041	-0.049
High	-0.002	-0.003	-0.003	-0.003	-0.004	-0.004
ΔW	-0.028	-0.046	-0.052	-0.064	-0.084	-0.115

Table 5: Welfare Effects of Price Variation and Structural Change

		Income elasticities				
		$\varepsilon_a = 0.79$	$\varepsilon_a = 0.83$	$\varepsilon_a = 0.86$	$\varepsilon_a = 0.91$	$\varepsilon_a = 0.95$
		(3)	(4)	(5)	(6)	(7)
Price Effect, *of which*	Low income	-0.024	-0.037	-0.055	-0.085	-0.127
	Lower-middle	-0.019	-0.029	-0.045	-0.071	-0.108
	Upper-middle	-0.006	-0.009	-0.014	-0.022	-0.033
	High	0.000	-0.001	-0.001	-0.001	-0.002
	World	-0.022	-0.033	-0.052	-0.082	-0.110
Structural change effect		-0.024	-0.018	-0.012	-0.002	-0.004

8. Policy implications

This study highlights key policy considerations. First, the findings underscore the need for policies that promote climate adaptation in agricultural practices and supply chain resilience. The findings suggest that climate shocks reduce global welfare by 4.6%, with disproportionate effects on low-income households due to their consumption patterns and income elasticity. Low-income countries often exhibit high income elasticity of demand for agri-food products, meaning that as incomes rise, their demand for these products increases more than proportionally. However,

if a climate shock disrupts supply and cannot meet growing demand, there may be a shift away from agriculture toward more resilient or less climate-sensitive sectors. The results suggest that to minimize welfare losses, it is critical to target these vulnerable sectors and invest in resilient agricultural practices to stabilize supply and ensure food security.

Second, countries need to continue reforming in terms of access to trade. Given that climate change shape comparative advantages, the results underscore the importance of international trade policies that account for shifting production patterns. For instance, reducing trade barriers on climate-resilient crops can help stabilize food supplies and mitigate price shocks.

Third, the differentiated impact of climate shocks on household welfare calls for strengthening social protection systems, such as conditional cash transfers and food assistance programs, to shield the most affected populations from food insecurity and income volatility.

9. Conclusion

This paper develops a multi-country Ricardian general equilibrium trade model with non-homothetic CES demand to quantify the welfare consequences of climate-induced agricultural productivity shocks. Relative to the existing literature, this paper departs from Nath (2025) by emphasizing the demand-side price channel rather than sectoral labor reallocation, and extends Costinot et al. (2016) by allowing for non-homothetic preferences and by decomposing welfare changes into price and structural-change components.

The results show that standard homothetic models substantially understate the welfare costs of climate change: once income effects on food demand are accounted for, estimated losses are considerably larger than under the homothetic benchmark. The decomposition of welfare changes into a price effect and a structural change effect reveals that the price channel, operating through the cost-of-living index, is the dominant driver of losses, while reallocation across sectors plays a comparatively minor role. Because lower-income countries devote a larger share of expenditure to food, they bear a disproportionate share of the welfare burden.

I show that international trade liberalization can partially offset these losses by easing access to food and improving the international allocation of agricultural production, though the magnitude of this mitigation remains modest relative to the scale of the underlying losses. The results suggest that policies aimed at stabilizing relative food prices and facilitating trade in agricultural products may be more effective at protecting household welfare than policies focused on longer-run structural adjustment. While the framework centers on a two-sector economy, it extends to multi-sector settings, particularly those in which labor mobility across sectors is imperfect, and offers a tractable approach for evaluating the distributional consequences of climate shocks.

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Appendix

A.1. Household's optimization problem

In each country, the representative agent derives utility from the consumption of the outside good C_j^o and the agricultural aggregate C_j^a, with preferences given by the Non-Homothetic CES utility function:

$$\sum_{b\in\{o,a\}} (\beta^b)^{\frac{1}{\alpha}} \left(\frac{C_j}{N_j}\right)^{\frac{\varepsilon^b(1-\alpha)}{\alpha}} \left(\frac{C_j^b}{N_j}\right)^{\frac{\alpha-1}{\alpha}} = 1, \tag{A.35}$$

where $U_j = E_j/P_jN_j = C_j/N_j$. The representative household maximizes U_j subject to the budget constraint:

$$E_j = \sum_b P_j^b C_j^b = w_jN_j + r_jL_j + D_j, \tag{A.36}$$

with $\sum_j D_j = 0$. The household's optimization problem implies that consumers select each good C_j^b, $b = \{a, 0\}$ that maximize aggregate consumption. The representative household's Lagrangian is:

$$\mathcal{L} = U_j + \rho\left[1 - \sum_b (\beta_b)^{\frac{1}{\alpha}} \left(\frac{C_j}{N_j}\right)^{\varepsilon_b\frac{(1-\alpha)}{\alpha}} \left(\frac{C_j^b}{N_j}\right)^{\frac{\alpha-1}{\alpha}}\right] + \Lambda\left[w_jN_j + r_jL_j + D_j - \sum_b P_j^bC_j^b\right]$$

with ρ and Λ the appropriate Lagrange multipliers. The first-order condition for C_j^b is:

$$0 = -\rho\,(\beta_b)^{\frac{1}{\alpha}} \left(\frac{C_j}{N_j}\right)^{\varepsilon_b\frac{(1-\alpha)}{\alpha}} \left(\frac{\alpha-1}{\alpha}\right) \left(\frac{C_j^b}{N_j}\right)^{\frac{\alpha-1}{\alpha}} \left(\frac{N_j}{C_j^b}\right) \left(\frac{1}{N_j}\right) - \Lambda\; P_j^b$$

$$\Rightarrow (\beta_b)^{\frac{1}{\alpha}} \left(\frac{C_j}{N_j}\right)^{\varepsilon_b\frac{(1-\alpha)}{\alpha}} \left(\frac{C_j^b}{N_j}\right)^{\frac{\alpha-1}{\alpha}} = \frac{\Lambda\alpha}{\rho(1-\alpha)} P_j^b\; C_j^b$$

using constraints 2 and 3 we get:

$$\frac{\rho(1-\alpha)}{\Lambda\alpha} = \sum_b P_j^bC_j^b = E_j \tag{A.37}$$

which further implies that:

$$(\beta_b)^{\frac{1}{\alpha}} \left(\frac{C_j}{N_j}\right)^{\varepsilon_b\frac{(1-\alpha)}{\alpha}} \left(\frac{C_j^b}{N_j}\right)^{\frac{\alpha-1}{\alpha}} = \frac{P_j^bC_j^b}{E_j} \tag{A.38}$$

Therefore, the optimal consumption of good C_j^b can be written as :

$$C_j^b = \beta_b \; N_j \left(\frac{P_j^b N_j}{E_j} \right)^{-\alpha} \left(\frac{C_j}{N_j} \right)^{\epsilon_b(1-\alpha)} \tag{A.39}$$

If we define P_j as the ideal consumer price index for the aggregate consumption of goods C_j, such that $E_j = P_j \; C_j$, then we have:

$$C_j^b = \beta_b \; N_j \left(\frac{P_j^b}{P_j} \right)^{-\alpha} \left(\frac{C_j}{N_j} \right)^{(1-\alpha)\epsilon_b+\alpha} \tag{A.40}$$

For agri-food products, we have :

$$C_j^a = \beta_a \; N_j \left(\frac{P_j^a}{P_j} \right)^{-\alpha} \left(\frac{C_j}{N_j} \right)^{(1-\alpha)\epsilon_a+\alpha} .$$

Multiplying both sides by $\frac{P_j^a}{P_j}$ results in an Engel equation that characterizes the share of spending allocated to agri-food products:

$$\frac{P_j^a C_j^a}{P_j} = \beta_a \left(\frac{P_j^a}{P_j} \right)^{1-\alpha} \left(\frac{C_j}{N_j} \right)^{(1-\alpha)(\epsilon_a-1)} (C_j) \tag{A.41}$$

$$\frac{P_j^a \; C_j^a}{P_j \; C_j} = \mathbf{s}_j^a = \beta_a \left(\frac{P_j^a}{P_j} \right)^{1-\alpha} \left(\frac{C_j}{N_j} \right)^{(1-\alpha)(\epsilon_a-1)} \tag{A.42}$$

The average cost of real consumption at the country level P_j measures changes in the cost of living in term of price and expenditure share and is given by :

$$P_j = \left[\sum_{b=\{o,a\}} \beta_b \; \left(P_j^b \right)^{1-\alpha} \; \left(\frac{C_j}{N_j} \right)^{(\alpha-1)(\varepsilon_b-1)} \right]^{\frac{1}{1-\alpha}} \tag{A.43}$$

As in Comin et al. (2021), I also express the price index P_j in terms of observables and demand parameters (proof in Appendix A.5). The homothetic CES specification corresponds to the special case of equation (A.43) in which $\varepsilon_b = 1 \quad \forall b \in \{o, a\}$.

A.2. Producer problem and land rents

I consider a parcel ω located in field f of country i. If this parcel is allocated to crop k, production is given by:

$$Q_i^{fk}(\omega) = A_i^{fk}(\omega) \min \left\{ L_i^{fk}(\omega), \frac{N_i^{fk}(\omega)}{\nu_i^f(\omega)} \right\}, \tag{A.44}$$

where $L_i^{fk}(\omega)$ denotes land used on the parcel, $N_i^{fk}(\omega)$ denotes labor, $A_i^{fk}(\omega)$ is parcel-level productivity, and $\nu_i^f(\omega)$ is the labor requirement. Land and labor are perfect complements.

The producer's optimization problem is to maximize land rent. For a given crop k, the producer chooses labor and land to maximize the surplus generated by the parcel:

$$\max_{L_i^{fk}(\omega),\, N_i^{fk}(\omega)} \left\{ p_i^k Q_i^{fk}(\omega) - w_i N_i^{fk}(\omega) \right\}. \tag{A.45}$$

Since the production technology is Leontief, it is never optimal to use excess labor relative to land. Therefore, whenever the parcel is operated, we have:

$$L_i^{fk}(\omega) = \frac{N_i^{fk}(\omega)}{\nu_i^f(\omega)}, \tag{A.46}$$

or equivalently,

$$N_i^{fk}(\omega) = \nu_i^f(\omega) L_i^{fk}(\omega). \tag{A.47}$$

Substituting equation (A.47) into (A.44), output becomes

$$Q_i^{fk}(\omega) = A_i^{fk}(\omega) L_i^{fk}(\omega). \tag{A.48}$$

The surplus generated by crop k on parcel ω is therefore

$$\Pi_i^{fk}(\omega) = p_i^k A_i^{fk}(\omega) L_i^{fk}(\omega) - w_i \nu_i^f(\omega) L_i^{fk}(\omega). \tag{A.49}$$

Equivalently,

$$\Pi_i^{fk}(\omega) = \left[p_i^k A_i^{fk}(\omega) - w_i \nu_i^f(\omega) \right] L_i^{fk}(\omega). \tag{A.50}$$

The term in brackets is the land rent per unit of land associated with crop k on parcel ω:

$$R_i^{fk}(\omega) = p_i^k A_i^{fk}(\omega) - w_i \nu_i^f(\omega). \tag{A.51}$$

Thus, the return to land is not an exogenous cost. It is the residual value of production after paying labor costs.

In the non-agricultural sector, I assume that labor is the only factor of production:

$$Q_i^o = A_i^o N_i^o, \tag{A.52}$$

where A_i^o denotes labor productivity in the non-agricultural sector and N_i^o is labor employed in that sector. The representative firm in the outside sector solves:

$$\max_{N_i^o} \Pi_i^o = P_i^o Q_i^o - w_i N_i^o. \tag{A.53}$$

Substituting equation (A.52) into (A.53) gives

$$\Pi_i^o = \left(P_i^o A_i^o - w_i\right) N_i^o. \tag{A.54}$$

Under perfect competition and constant returns to scale, equilibrium profits are zero whenever the outside good is produced. Hence,

$$P_i^o A_i^o - w_i = 0, \tag{A.55}$$

which implies

$$w_i = P_i^o A_i^o. \tag{A.56}$$

Since the outside good is freely traded and used as the numeraire, its price is normalized to one:

$$P_i^o = 1. \tag{A.57}$$

Therefore,

$$w_i = A_i^o. \tag{A.58}$$

This condition means that the wage is pinned down by labor productivity in the freely traded non-agricultural sector.

Plugging (A.58) into (A.51), the land rent can be written as

$$R_i^{fk}(\omega) = p_i^k A_i^{fk}(\omega) - A_i^o \nu_i^f(\omega). \tag{A.59}$$

A.3. Crop choice and land allocation

The producer allocates the parcel to the crop that generates the highest non-negative land rent. Since $\nu_i^f(\omega)$ does not vary across crops within a given parcel, the labor-cost term is common across crops. Therefore, conditional on cultivation, the crop choice depends on the value of marginal product, $p_i^k A_i^{fk}(\omega)$.

A parcel is cultivated with crop k only if the value of producing crop k on that parcel exceeds both the value of producing any other crop on the same parcel and the labor cost required to operate the parcel. Formally, this requires:

$$p_i^k A_i^{fk}(\omega) > p_i^\ell A_i^{f\ell}(\omega) \qquad \forall \ell \neq k, \tag{A.60}$$

and

$$p_i^k A_i^{fk}(\omega) > A_i^o \nu_i^f(\omega). \tag{A.61}$$

Equivalently, crop k is chosen on parcel ω if and only if

$$p_i^k A_i^{fk}(\omega) = \max\left\{A_i^o \nu_i^f(\omega), p_i^1 A_i^{f1}(\omega), \ldots, p_i^K A_i^{fK}(\omega)\right\}. \tag{A.62}$$

The share of field f allocated to crop k is therefore

$$\pi_i^{fk} = \Pr\left[p_i^k A_i^{fk}(\omega) = \max\left\{A_i^o \nu_i^f(\omega), p_i^1 A_i^{f1}(\omega), \ldots, p_i^K A_i^{fK}(\omega)\right\}\right]. \tag{A.63}$$

Following Costinot et al. (2016), parcel-level productivity and labor requirements are unobserved and independently drawn from Fréchet distributions[4] with a common shape parameter $\theta > 1$. The GAEZ data provide the average field-crop productivity $A_i^{fk} = E\left[A_i^{fk}(\omega)\right]$. The labor-cost component $A_i^o \nu_i^f(\omega)$ is summarized by a country-specific scale parameter

$$a_i \equiv A_i^o \nu_i, \tag{A.64}$$

where ν_i denotes the average labor requirement in agriculture.

Using the properties of the Fréchet distribution, the probability in (A.63) becomes

$$\pi_i^{fk} = \frac{\left(p_i^k A_i^{fk}\right)^\theta}{a_i^\theta + \sum_{\ell \in \mathcal{K}} \left(p_i^\ell A_i^{f\ell}\right)^\theta}. \tag{A.65}$$

The supply side is disciplined by two parameters: the within-field productivity dispersion parameter θ and the country-specific labor-cost shifter a_i. The former governs the strength of comparative advantage and the elasticity of land allocation across crops, while the latter controls the extent to which land is profitably cultivated. These parameters are calibrated in the

[4]Following Costinot et al. (2016), the random variables $A_i^o \nu_i^f(\omega), p_i^1 A_i^{f1}(\omega), \ldots, p_i^K A_i^{fK}(\omega)$ are independent Fréchet random variables with common shape parameter $\theta > 1$. The scale parameter of $Z_k(\omega)$ is $p_i^k A_i^{fk}$, while the scale parameter of the labor-cost threshold $Z_0(\omega)$ is $a_i \equiv A_i^o \nu_i$, where ν_i summarizes the average labor requirement in agriculture.

empirical implementation.

A.4. Supply of crop

The Leontief specification indicates that, conditional upon the exploitation of the plot, output is equal to land productivity multiplied by the cultivated surface area. The Aggregate output of crop k in country i is obtained by summing production over all fields.

$$Q_i^k = \sum_f \int_0^1 Q_{ifk}(\omega) d\omega \tag{A.66}$$

For a given field f, let s_{if} denote the field's surface and π_i^{fk} the share of that field allocated to crop k. Production in field f for crop k is therefore given by the amount of land allocated to crop k, $s_{if}\pi_i^{fk}$, multiplied by the average productivity of parcels selected into crop k:

$$Q_i^{fk} = s_{if}\pi_i^{fk} E\left[A_i^{fk}(\omega) \mid k \text{ is chosen}\right]. \tag{A.67}$$

Under the Fréchet assumption, the expected productivity of parcels allocated to crop k is

$$E\left[A_i^{fk}(\omega) \mid k \text{ is chosen}\right] = A_i^{fk}\left(\pi_i^{fk}\right)^{-1/\theta}. \tag{A.68}$$

Substituting equation (A.68) into (A.67) gives

$$Q_i^{fk} = s_{if}\pi_i^{fk} A_i^{fk}\left(\pi_i^{fk}\right)^{-1/\theta}. \tag{A.69}$$

Therefore,

$$Q_i^{fk} = s_{if} A_i^{fk}\left(\pi_i^{fk}\right)^{\frac{\theta-1}{\theta}}. \tag{A.70}$$

Using equation (A.70), (A.66) becomes

$$Q_i^k = \sum_{f\in\mathcal{F}_i} s_{if} A_i^{fk}\left(\pi_i^{fk}\right)^{\frac{\theta-1}{\theta}}. \tag{A.71}$$

Finally, substituting the land-allocation share equation (A.65) into equation (A.71) yields:

$$Q_i^k = \sum_{f\in\mathcal{F}_i} s_{if} A_i^{fk}\left[\frac{\left(p_i^k A_i^{fk}\right)^\theta}{a_i^\theta + \sum_{\ell\in\mathcal{K}}\left(p_i^\ell A_i^{f\ell}\right)^\theta}\right]^{\frac{\theta-1}{\theta}}. \tag{A.72}$$

A.5. Price index with Non-homothetic CES preferences

The non-homothetic CES price index depends on the consumer's utility level, which is generally unobservable. To address this challenge, I rely on expenditure shares, which are observable at the country level. The consumer's utility level is implicitly derived from the following equation:

$$\sum_{b=\{o,a\}} (\beta_b)^{\frac{1}{\alpha}} \left(\frac{C_j}{N_j} \right)^{\varepsilon_b \frac{(1-\alpha)}{\alpha}} \left(\frac{C_j^b}{N_j} \right)^{\frac{\alpha-1}{\alpha}} = 1 \tag{A.73}$$

Such that:

$$\mathbf{s}_j^b = \beta_b \left(\frac{P_j^b}{P_j} \right)^{1-\alpha} \left(\frac{C_j}{N_j} \right)^{(1-\alpha)(\epsilon_b - 1)} \quad , \tag{A.74}$$

and

$$P_j^{1-\alpha} = \frac{\beta_b}{\mathbf{s}_j^b} \left(P_j^b \right)^{1-\alpha} \left(\frac{C_j}{N_j} \right)^{(1-\alpha)(\epsilon_b - 1)} \tag{A.75}$$

Taking logarithms yield:

$$\log P_j = \frac{1}{1-\alpha} \left[\log \beta_b - \log \mathbf{s}_j^b \right] + \log P_j^b + (\epsilon_b - 1) \log \left(\frac{E_j}{P_j \ N_j} \right) \tag{A.76}$$

Applying the sum, we have:

$$\sum_b \log P_j = \frac{1}{1-\alpha} \sum_b \left[\log \beta_b - \log \mathbf{s}_j^b \right] + \sum_b \log P_j^b + \sum_b (\epsilon_b - 1) \log \left(\frac{E_j}{P_j \ N_j} \right) \tag{A.77}$$

Averaging across sectors gives:

$$\log P_j = \frac{1}{1-\alpha} \log \tilde{\beta} - \frac{1}{1-\alpha} \log \tilde{\mathbf{s}}_j + \log \tilde{P}_j + \psi \log \left(\frac{E_j}{P_j \ N_j} \right) \ , \tag{A.78}$$

where a tilde above each variable denotes an average across sectors such that $\tilde{P}_j = \left(\prod_{b \in B} P_j^b \right)^{\frac{1}{\texttt{Card}(\mathbf{B})}}$, $\psi = \frac{1}{\texttt{Card}(\mathbf{B})} \sum_b (\epsilon_b - 1)$, and $\mathbf{B}$ is the set of elements indexed by b, or the total number of sectors. Therefore:

$$(1+\psi) \log P_j = \frac{1}{1-\alpha} \log \tilde{\beta} - \frac{1}{1-\alpha} \log \tilde{\mathbf{s}}_j + \log \tilde{P}_j + \psi \log \left(\frac{E_j}{N_j} \right) \tag{A.79}$$

Finally, we have :

$$P_j = \tilde{\beta}^{\frac{1}{(1+\psi)(1-\alpha)}} \tilde{P}_j^{\frac{1}{(1+\psi)}} \tilde{\mathbf{s}}_j^{-\frac{1}{(1+\psi)(1-\alpha)}} \left(\frac{E_j}{N_j} \right)^{\frac{\psi}{1+\psi}} \quad , \tag{A.80}$$

A.6. Sample Coverage

Table A.6: Crops and Share of World Crop Output Value

Crop	Share of world crop output (%)
Rice	16.83
Maize	11.03
Wheat	10.38
Cotton	6.47
Tomato	5.70
White Potato	5.47
Soybean	5.44
Sugarcane	4.52
Banana	3.08
Oil Palm	2.87
Total	71.79

Source: FAOSTAT. Shares computed over the 50-country sample.

Table A.7: Countries by Income Group and Share of World Crop Output Value

Low income		Lower-middle income		Upper-middle income		High income	
Country	%	Country	%	Country	%	Country	%
Congo	0.41	Burma	1.63	China	22.13	Poland	0.40
Malawi	0.41	Bangladesh	0.78	Thailand	1.28	Korea, Rep.	1.00
Ethiopia	0.53	Viet Nam	1.92	Ecuador	0.4	Greece	0.79
Tanzania	0.58	Ghana	0.48	Algeria	0.41	Spain	1.14
Uganda	0.70	Uzbekistan	0.75	Colombia	0.63	United Kingdom	0.50
		Pakistan	1.23	Iran	0.82	Canada	1.14
		India	9.21	Kazakhstan	0.36	Japan	2.92
		Cameroon	0.4	South Africa	0.38	Germany	1.07
		Côte d'Ivoire	0.4	Malaysia	0.59	Australia	1.03
		Nigeria	3.04	Russia	1.99	Italy	0.96
		Sudan	0.41	Brazil	4.87	United States	9.05
		Philippines	0.82	Argentina	1.44	Netherlands	0.40
		Indonesia	4.05	Romania	0.44	France	1.19
		Ukraine	0.81	Mexico	0.90		
		Egypt	0.95	Venezuela	0.71		
		Morocco	0.37	Turkey	2.35		

Notes: Income group classification follows the World Bank 2011 classification. Source: FAOSTAT and World Bank data.

A.7. Sensitivity

Table A.8: Sensitivity of structural parameters to alternative values of the cross-sector elasticity of substitution α

α	ε_a	β_a	β_o
0.30	0.857	0.705	0.295
0.40	0.833	0.705	0.295
0.50	**0.799**	**0.705**	**0.295**
0.60	0.749	0.705	0.295
0.70	0.666	0.705	0.295
0.80	0.499	0.705	0.295

Notes: Each row reports structural parameters implied by the estimated reduced-form coefficients from equation (26). Note that β_a and β_o do not vary with α since they are identified from the intercept $\hat{b}_0$. Engel's law requires $\varepsilon_a < 1$, which holds across all specifications.