Diet, Economic Development and Climate Change

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Abstract

We study the impact of economic development on greenhouse gas emissions (GHG) from agriculture. We document the environmental implications of two agricultural transformations linked to economic development. First, a shift in consumer demand to food products with higher GHG emissions. Second, the adoption of modern, input-intensive technologies with high levels of GHG emissions. We incorporate these mechanisms in a quantitative, trade model by featuring different income elasticities of demand across food products, and multiple agricultural technologies for production across grid-cells covering the surface of the Earth, with food products and technologies being heterogeneous in their GHG emission intensity. Using the model's open economy structure, we prove that the income elasticities are identified without price data. We conduct a host of policy counterfactuals related to economic growth, trade policies, and sustainable diets. The GHG emissions from economic growth is understated by more than one third if diet and technology changes are shut down, and overstated by one hundred percent if global food supply readjustments are ignored. Compared to food trade policies, dietary restrictions are both substantially more effective in reducing GHG emissions, and more favorable when considering the welfare losses in developing countries.

Keywords: Diet, Economic Development, Calorie Consumption, Climate Change

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1 Introduction

Food production is a critical factor in climate change, accounting for approximately one-third of global greenhouse gas (GHG) emissions (Crippa et al., 2021; IPCC, 2022). Moreover, richer nations contribute disproportionately to these emissions, notably due to their typically meat-intensive diets and intensive use of farm machinery and fertilizers (McDermid et al., 2023; Tilman et al., 2002, 2011). This raises concern that, as the rest of the world continues to grow economically, their GHG emissions from food production will catch up to the emissions from developed countries, exacerbating global climate change.

Several factors, however, contribute to higher agricultural emissions in richer countries. Some of these factors might intensify the GHG emissions of poorer countries as they experience economic development, such as the shift in their diets from cereal dominance to meats, fruits and vegetables—a process known as the nutrition transition (Subramanian and Deaton, 1996; Deaton and Drèze, 2009)— or the intensification of the use of inputs such as fertilizers and machinery—which is referred to as agricultural modernization (Johnston and Mellor, 1961; Schultz et al., 1968; Gollin et al., 2007; Farrokhi and Pellegrina, 2023). Other factors, such as dietary preferences, comparative advantage in certain crops, or a country's geographic location, may persist regardless of economic development. Understanding the role of economic development on food emissions requires a framework that allows one to account for the influence of these different factors.

This paper studies the relationship between diet and GHG emissions from agriculture, and how this relationship is transformed by economic development. We develop a quantitative, multi-country, general equilibrium model that incorporates the environmental implications of agricultural modernization and nutritional transition. To quantify our model, we bring together several data sources, resulting in a rich, cross-country dataset with information on calorie intake and GHG emissions (in tons of CO2 equivalent) from food production. Exploiting the open economy structure of the model, we prove that identification of the food product income elasticities, which are key for the nutrition transition, does not require price data. We use our quantified model to measure the contribution of economic development to the observed agricultural emissions across countries, and to evaluate the impact on global agricultural emissions of economic growth, dietary restrictions and food trade policies.

We start by documenting four empirical patterns about agricultural GHG emissions, and economic development. First, GHG emissions vary considerably across countries due to differences in their diet composition, suggesting significant implications for global GHG emissions. For example, if the entire world adopted the US diet composition of food products while maintaining their same calorie intake, the share of global GHG emissions from agriculture would increase by 12 percentage points, an increase of 40 percent. Second, GHG emissions *per capita* and *per kcal* from food consumption increase strongly with GDP per capita. Third, food products with higher levels of GHG emissions per kcal have higher income elasticities. This implies that as countries become wealthier, their diets shift towards environmentally harmful products, highlighting the environmental implications of the nutrition transition.[1] Fourth, the share of emissions from fertilizers and energy use relative to total emissions from food production rises with GDP per capita. This *within product* variation, in contrast to the *between product* variation in pattern three, underscores the environmental implications of agricultural modernization.

We construct our model motivated by these empirical patterns. On the demand side, households have a nested, non-homothetic CES preference structure with many goods, which allows for differences in income elasticities across food products. On the supply side, based on Farrokhi and Pellegrina (2023), we feature highly granular grid-cells covering the entire surface of the Earth. Each cell hosts an agricultural producer choosing which food product to produce on a plot and whether to employ a modern or a traditional agricultural technology. In the model, GHG emissions from agriculture comes from food production and food transportation. In particular, differences in GHG emissions from food production across countries arise from differences in the food-product composition and in the adoption of modern technologies. We provide a first order approximation result that highlights the different mechanisms driving the relationship between country-level emissions from food production and economic development.

We quantify the model as follows. We start by developing an estimation strategy of the income elasticities that generalizes the method used in the literature (e.g., Comin et al. 2021) to nested CES preferences and to an open-economy model. Notably, we prove that unlike in the closed-economy version, the income elasticities are identified without without price data. Specifically, trade shares can be used to construct a sufficient statistic for the prices experienced by a representative consumer in that country. We then estimate the technological parameters governing the GHG emissions by food product and agricultural technology using product- and country-level data on GHG emissions. The rest of the parameters are calibrated as in the literature. Reassuringly, our quantified model replicates key relationships between GHG emissions, economic development and agricultural technology use in the data.

We first use our quantified model to understand the drivers of the observed, strongly increasing relationship between food GHG emissions per capita and GDP per capita across countries. We find that about two-thirds of the correlation is driven by intrinsic diet pref-

[1] In particular, we find that this relationship persists even if we do not consider meat consumption, as vegetables and fruits tend to emit more per calories than staple foods like yam and potatoes.

erences (reflecting for example culture or demographics), rather than GDP per capita. We perform the same exercise for the relationship between GHG per kcal and GDP per capita and find that diet preferences account for half of the slope observed in the data. This reveals that the effect of economic growth on GHG emissions would be less than the observed correlations would suggest.

We second simulate the model to conduct a host of policy counterfactuals related to future economic growth, dietary restrictions and food trade policies. For each counterfactual, we perform decompositions to quantify the contribution the nutrition transition, agricultural modernization, transportation and general equilibrium adjustments in supply. We find that economic growth induced by a 10 percent increase in the overall productivity of an economy generates a substantial increase in GHG emissions of 5.0 percent (or 0.2 Gt CO2). The nutrition transition and agricultural modernization are quantitatively important in the case of economic growth, with the effect on emissions being understated by a bit more than one third if we shut down these two channels. Emissions from transportation are not quantitatively important as it accounts for only five percent of global emissions. We find that ignoring the equilibrium responses in supply would overstate the impact of economic growth on GHG emissions by approximately 100 percent, showing the importance of having a framework that allows for supply and demand interactions.

Our results show that dietary policies can substantially reduce GHG emissions—though, we find that back-of-the-envelope calculations, those that ignore the equilibrium responses in supply, tend to substantially overstate their impact by about one third. If the entire world adopted a no-beef diet, our model implies that global GHG emissions from agriculture would drop by 20 percent, and if the entire world adopted a vegetarian diet, emissions would drop by 20 percent. Global welfare losses tend to be limited up to 2.8%, with poorer countries being impacted more. For instance, Argentina and Uruguay experience welfare losses up to 5 percent in the case of no beef, given they are large meat producers and consumers. Trade policies, conversely, generate large welfare losses across the world, with even greater inequality across rich and poor countries, and with smaller benefits in terms of GHG emissions. If there was no international trade in agricultural output, countries in the bottom quartile of the GDP per capita distribution would experience a 41 percent reduction in their welfare. Global GHG emissions would decline by 11.9 percent. Our results therefore indicate that dietary policies can have much larger effects on GHG emissions than food trade policies.

The outline of the paper is as follows. We first review the literature in the remainder of this section. Section 2 describes our data and present the empirical patterns. Section 3 presents our quantitative model. Section 4 quantifies the model and present the methodology for the estimation of income elasticities without price data. Section 5 presents the results from our quantitative exercises. Section 6 concludes.

Related Literature. This paper contributes to economic research on climate change, primarily by evaluating the role of the nutrition transition and agricultural modernization on GHG emissions, both of which we find to be quantitatively important. First, and most closely, our work relates to papers focusing on the interaction between climate and the agricultural sector, such as Conte et al. (2021), Gouel and Laborde (2021), Costinot et al. (2016), Nath (2022), Dominguez-Iino (2021), Farrokhi et al. (2023), and Hsiao (2021). In terms of modeling agricultural production, we build on Costinot et al. (2016), who developed a framework in which agricultural production comes from grid-cells across the world, and from Farrokhi and Pellegrina (2023), who generalize Costinot et al. (2016) to allow for multiple agricultural technologies. Furthermore, we incorporate non-homothetic preferences across food products and provide a new identification result, so building on the expanding literature utilizing these preferences (Comin et al., 2021; Sposi et al., 2021; Caron and Fally, 2022; Cruz, 2023).

Second, and more broadly, we contribute to growing research using quantitative spatial models to study climate change (see Desmet and Rossi-Hansberg, 2024 and Shapiro and Balboni, 2024 for recent surveys). This literature has studied the impact of climate change on economic activity (Balboni, 2019; Bilal and Rossi-Hansberg, 2023; Burzyński et al., 2022; Cruz and Rossi-Hansberg, 2024; Cruz, 2023; Desmet et al., 2018; Conte et al., 2021), the impact of trade on CO2 emissions (Shapiro, 2016; Akerman et al., 2024), and the role of trade policy and carbon taxes (Farrokhi and Lashkaripour, 2021; Conte et al., 2022). We provide a host of new counterfactual results on the impact of economic development on GHG emissions from agriculture, a critical sector for climate change and for welfare in developing countries. To the best of our knowledge, we are the first to analyze the impact of dietary restrictions and food trade policies on agricultural emissions within this broad literature.

By bringing in the role of diet to quantitative trade models, our paper also speaks to the classic work on the relationship between nutrition and economic development. In the seminal paper Subramanian and Deaton (1996), it is shown that the price of food per calorie increases with income, which can be interpreted as a shift to food products with higher value added, a form of nutrition transition (Drewnowski and Popkin, 1997; Du et al., 2004; Keyzer et al., 2005; Bellemare et al., 2024). In addition, by incorporating technological choices in our framework, our paper relates to classic research on the role of agricultural modernization on economic development (Johnston and Mellor, 1961; Schultz et al., 1968; Gollin et al., 2007). Here, we uncover the environmental implications of these two central phenomena in economic development by bringing them to a quantitative trade model.

Lastly, we complement an extensive and rich literature in environmental science evaluating the impact of agriculture on emissions (Wallén et al. 2004; Carlsson-Kanyama and González 2009; Hoolohan et al. 2013; Perignon et al. 2017; see McCarl and Hertel, 2018 for an overview of studies on this topic). Within this literature, several papers have studied the environmental implications of the nutrition transition using food demand projections (Hoolohan et al., 2013; Perignon et al., 2017; Hale et al., 2024).[2] This line of research typically abstracts from general equilibrium adjustments in agricultural production costs and price, which we account for in our framework. Notably, we find that supply side reactions can substantially limit the impact of the food demand growth on GHG emissions.[3]

2 Data and Empirical Patterns

Our dataset contains 90 countries, plus a representative country for the rest of the world, and 47 food products for 2010. For each country, we construct information on calories intake by food product, GHG emissions from food production and consumption, bilateral trade flows and gross output by sector. For each food product, we gather grid-level data on potential yields for more than 1 million grids across the Earth.[4] For a subset of countries, we collect household level data with information on consumption. In this section, we describe our data and present four empirical patterns relating calories intake, GHG emissions, and economic development.[5]

2.1 Data

GHG emissions. There are two major datasets used to study GHG emissions from food production at a global scale, both of which we use in our analysis. The first dataset comes from Poore and Nemecek (2018) (hereafter, PN18). This is the largest meta-analysis of food systems to date and represents the state of the art in terms of the measurement of global GHG emissions by food product. Specifically, the authors collect information from more

[2] Tilman et al. (2011) in particular project the demand for food to evaluate the impact on GHG emissions. They consider scenarios in which different agricultural technologies are exogenously adopted across the world, without endogenizing technological choices as we do.

[3] One exception is Chen et al. (2022), who incorporate such general equilibrium adjustments using a computable general equilibrium (CGE) model that is designed for climate policy. Relative to our paper, theirs consider a substantially smaller number of food items, limiting the scope of the nutrition transition, and they do not feature multiple agricultural technologies.

[4] For the time being, for computational reasons, we are utilizing 100 fields per country. We will use the entire set of fields in the next iteration of the paper.

[5] Appendix OA describes our data construction in detail.

than 1500 studies to construct measures of GHG emissions for more than 80 food products, representing 90% of the protein and calorie intake worldwide. From this dataset, we obtain measures of the average global GHG emissions by food product. We build crosswalks to match the food products from PN18 to the food products in our data on calories intake and bilateral trade flows. These data shows large variation in the GHG emissions per kcal across food products. For example, meat and coffee generates more than 35 kilos of CO2 per 1000 kcal, whereas wheat and rye produce less than 5 kilos of CO2 per 1000 kcal — see Appendix Figure O.1.

The second dataset is the Emissions Database of Global Atmospheric Research (EDGAR-FOOD), which is constructed by Crippa et al. (2021). This dataset provides cross country-level information on CO2 emissions by stages of the agricultural supply chain — e.g., production, processing, transportation, and packaging. These data are designed to be consistent with Food and Agriculture Organization Corporate Statistical Database (FAO-STAT), which we utilize for information on agricultural production, trade and consumption. Importantly, these data allows us to measure, separately, the GHG emissions generated by the transportation of food from the GHG emissions produced in other stages of the food supply chain.[6]

Using these two datasets, we obtain three measures of GHG emissions. First, a measure of emissions from food *production* by country and, second, a measure of global emissions from food *transportation*, both of which come from EDGAR-FOOD. (In our data, about 95% percent of the GHG emissions from agriculture come from production, representing 16.5 Gt CO2, whereas emissions from food transport account for 5 percent of global GHG emissions, representing 0.7 Gt CO2.) Third, we construct a measure of emissions from food *consumption* by country-product, which is the caloric intake by food product multiplied by the average global emissions by calories from that food product (PN18).[7]

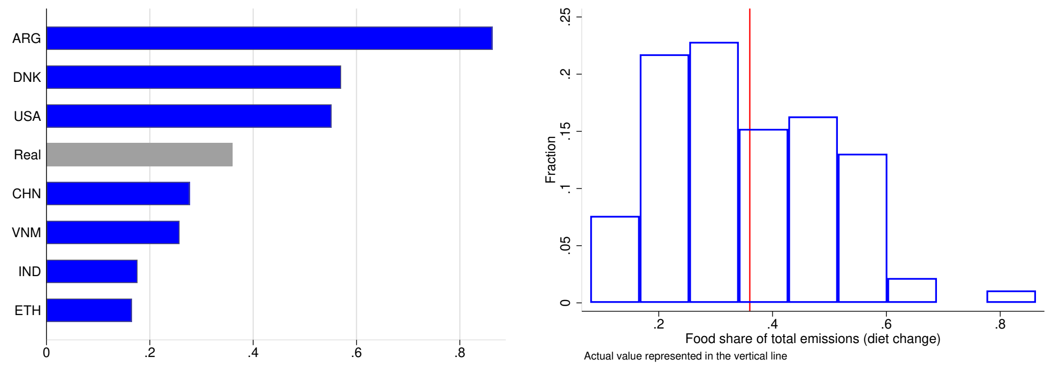
Trade and production. Our data on calorie intake by country and food product come from the Food and Agriculture Organization (FAO) Food Balance Sheets (FBS), which is a a special annual report produced by FAO since the 1960s that focuses on calorie consumption

[6]Since both of these two datasets (EDGAR-FOOD and PN18) do not measure GHG emissions from different agricultural technologies, we complement them with data from FAO-STAT on GHG emissions from fertilizer and energy use, which we use in empirical pattern 4.

[7]This is an implied measure of GHG emissions that does not take into account whether the food product that was consumed in a given country was produced with or without a GHG-intensive technology. Since the food products produced with different technologies are the same from the point of view of the consumer (and especially in the data), we are unable to take the technology dimensions into account when constructing the GHG emissions from food consumption. As such, by construction, differences in GHG emissions across countries from food consumption are not affected by differences in the technology used for production. In constructing these measures, we ensure that the total emissions from food consumption equals the the total emissions from food production plus from food transportaion. As such, our measure of food emissions from consumption capture the role of international trade in generating emissions from agriculture.

Figure 1: Implied global GHG emissions from each countries' diet

(a) Food share of total emissions (b) Distribution across countries



Notes: We calculate the share of GHG emissions from food consumption relative to total GHG from all sectors by changing the share of calories intake derived from each food product of all countries in the world to that of a particular country, *while holding fixed total calories consumed by country*. Panel (a) shows results for selected countries and Panel (b) the distribution of shares in GHG emissions for each considered diet. The grey bar in Panel (a) represents the baseline share of GHG emissions from food consumption. Figures are based on data from 2010.

across the world. These are measures of apparent consumption of calories (i.e., production minus exports plus imports plus adjustments for stock), available in terms of per capita dietary energy supply (kcal/cap/day)—often referred to as DES in the literature. From the FBS, we also obtain conversion factors to transform every quantity of food produced from calories to weight (adjusted by edible portion of the food product), which we later employ to compute the emissions from transportation.

Bilateral trade flows and revenues by food product come from FAO-STAT, value added by sector (agriculture and non-agriculture) from the United Nations, consumption share in agriculture from the World Bank, and GDP per capita from the Penn World Tables. We bring in potential yield by food product and technology from FAO-GAEZ, which is available for approximately 1.1 million fields across the world — see Appendix Figure O.2. The key feature of these data is that it is constructed based solely on the agro-climatic conditions of a region grid-cell, without incorporating any local market conditions.

Household expenditure. To bolster our results related to the patterns of food consumption by income, we additionally collect household consumption data. Specifically, we use the Brazilian Consumer Expenditure Survey, POF, which is a household expenditure survey data conducted by the Brazilian census bureau, IBGE.

2.2 Empirical Patterns

Empirical Pattern 1. GHG emissions from food consumption per capita vary considerably across each country's diet. We start with a back-of-the-envelope calculation that shows that diet changes have the potential to considerably impact global GHG emissions. Holding fixed each countries' total number of calories intake, we change the composition of these calories to that of another country (i.e. the same proportions of beef, rice, etc), and calculate the new share of total emissions given by food across the world. Figure 1 reports results from this exercise. The factual food share of total emissions across the world is approximately 30%. Whereas, if the whole world adopts the diet of the USA, while keeping total calories unchanged, the food share of total emissions across the world rises to 42% — see Figure 1a. This can rise as high as 74% if the whole world adopts the Argentinian diet, and fall as low as 12% if the Ethiopian diet is adopted. Figure 1b presents the distribution of these counterfactual shares across all countries.

This exercise suggests that changing the composition of diet alone, without changing the total amount of calories, has the potential to considerably impact global GHG emissions. However, this exercise is effectively partial equilibrium, as it implicitly assumes there are no changes in prices or incomes as a result of the changes in demand for food products due to diet change. This is an unrealistic assumption, as presumably the food prices should react across countries, and general equilibrium effects will shape aggregate outcomes. This motivates the use of a quantitative model to account for these economic mechanisms.

Empirical Pattern 2. GHG emissions from food consumption per capita increases with GDP per capita. Panel (a) in Figure 2 shows a strong positive correlation between GHG emissions from food consumption per capita and GDP per capita: a 1 percent increase in GDP per capita is associated with a 0.34 percent increase in emissions. This relationship captures, at least in part, a scale effect: as countries get richer, they consume more food, which mechanically increases the GHG emissions from food consumption — for example, in the data the US has a dietary energy intake of 3745 kcal/cap/day and Tanzania of 2310 kcal/cap/day.[8] Indeed, Panel (b) shows a strong positive correlation between calories consumed per capita and GDP per capita, which is consistent with findings in the literature (Tilman et al., 2011; Subramanian and Deaton, 1996). Specifically, a 1 percent increase in GDP per capita is associated with a 0.11 percent increase in calories per capita. Thus, the scale effect contributes about one third of the correlation in Panel (a). The remainder is due

[8] The estimated relationship is approximately log-linear across different levels of economic development. One could hypothesize an inverse-U shape — the Environmental Kuznets Curve — reflecting a decline in emissions as countries get very rich, perhaps due to the adoption of more sustainable diets or governmental policies. We find, however, no evidence of this phenomenon, like much of the literature (Dinda, 2004).

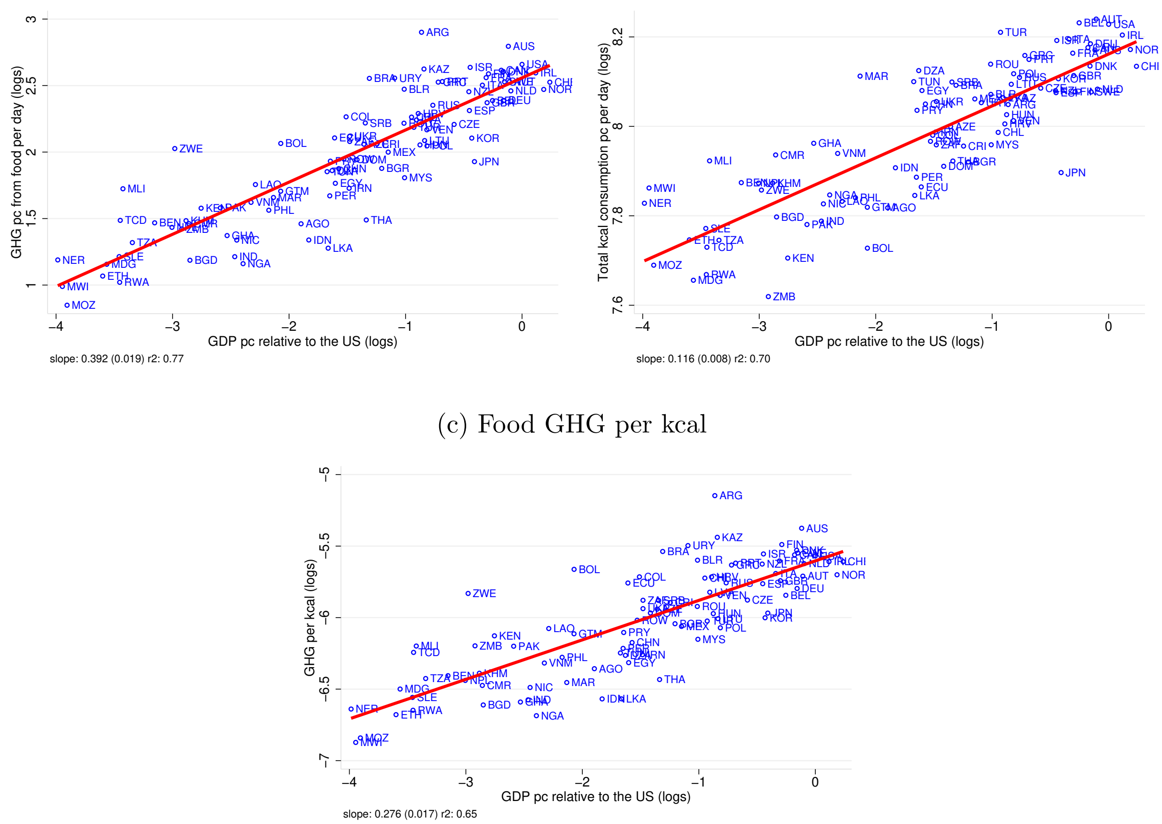
to a compositional effect: richer economies consume calories from food products associated with higher GHG emissions per calorie. We see this in Panel (c), where we plot food GHG emissions *per calorie* against GDP capita. A 1 percent increase in GDP per capita is associated with a 0.23 percent increase in the emissions per calorie consumed, which accounts for the remaining two thirds of the correlation.

Figure 2: GHG Emissions from Food Consumption, Calories Intake, and GDP per capita

(a) Food GHG per capita

(b) Calories per capita

(c) Food GHG per kcal



Notes: This figure shows the relationship between GHG emissions, calories and economic development. We construct GHG from food consumption per day by multiplying calories intake by food product by the average emissions from that food product. Best linear fit presented in red.

This decomposition reveals that the food products consumed in richer economies are associated with greater GHG emissions. In the third empirical pattern, we provide evidence suggesting that the nutrition transition help explain this relationship. In the fourth and last empirical pattern, we turn to food production and show the environmental implications of the agricultural modernization.

Empirical Pattern 3. Agricultural goods with higher levels of GHG emissions have higher income elasticities. We next turn to the environmental implication of the nutrition transition (Tilman et al., 2011; Subramanian and Deaton, 1996). This mechanism operates *between* food products and arises in consumer demand: richer countries have preference for products that happen to emit more GHG emissions. We investigate this here by providing reduced-form estimates of the income elasticities for each food product, and correlating them with the product's GHG emission intensity. In Section 3.4, we revisit these estimates in light of our quantitative model. We use both cross-country level data as well as household surveys, and following the literature, alleviate endogeneity of income by using fixed effects to control for prices and preference shifters (Aguiar and Bils, 2015; Comin et al., 2021).

Cross-country Estimates. We estimate:

$$E_{j,k,t} = \underbrace{\tilde{\delta} \cdot \mathrm{GHGpk}_k}_{\equiv \delta_k} \cdot \mathrm{GDPpc}_{j,t} + \gamma_{k,t} + \kappa_{j,t} + \varepsilon_{j,k,t} \tag{1}$$

where $E_{j,k,t}$ is country j log expenditure on product k from all countries ("absorption") in period t. The coefficient, δ_k, on log GDP per capita in country j, $\mathrm{GDPpc}_{j,t}$, is the income elasticity of product k. We parameterize this as a function of CO2 emissions per kilo-calorie of good k, $\delta_k = \tilde{\delta} \cdot \mathrm{GHGpk}_k$, to directly test the relationship between the income elasticities and emissions across products. $\tilde{\delta}$ captures in a reduced-form way how income elasticities interact with the levels of emissions per capita per product.

For δ_k to identify an income elasticity, we need to control for changes in price and other demand factors that are correlated with GDPpc. The fixed effects go some way to ensuring this. The product-time fixed effect $\gamma_{k,t}$ captures any global factors, such as due to product-specific technological progress or effects of climate change. The country-time fixed effect captures any country-specific factors, such as due to regional technological change or diet preference. There may be remaining factors of concern (such as product and region specific technological change). Reassuringly, the results are similar to those from our structural estimation in section 4.1.1, in which we use the functional form of our quantitative model to control for all endogeneity arising through prices.

Table 1 reports our results for $\tilde{\delta}$. Column (1) is the baseline, while column (2) excludes meat products ("Beef", "Lamb and Mutton", "Pig meat", "Poultry"). Our results are quantitatively similar in each case: a 1 percent increase in GHGpk_k is associated with a highly significant 0.25 percent increase in the income elasticity of good k. That indicates that much of the focus on meat consumption misses the transition of diet towards vegetables and fruits when countries experience economic growth, which also amplifies the GHG emissions from food consumption. Figure 3 shows our results for δ_k (with k = Yam normalized to zero), the estimates of the relative levels of the income elasticities across products, illustrating the

Table 1: Income Elasticity and GHG Emissions per calorie

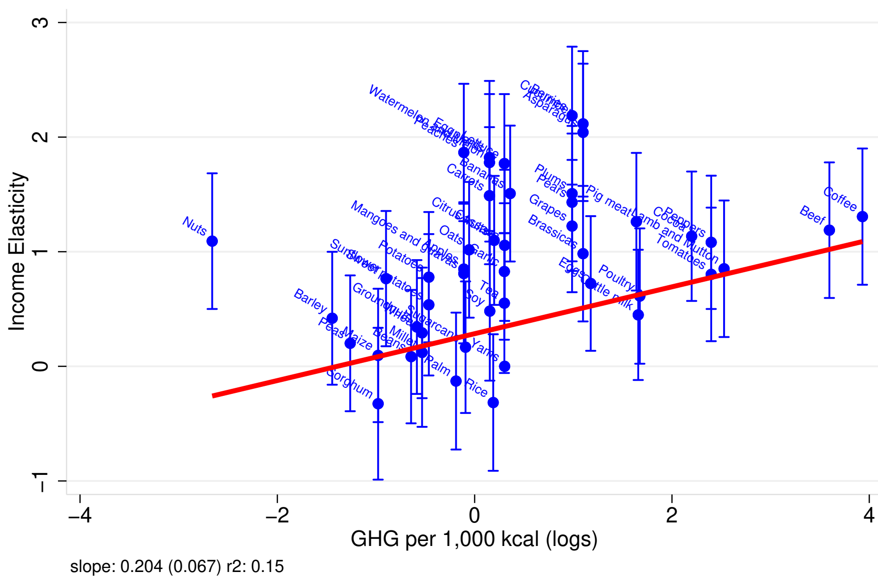
	All crops		No meat	
	(1)	(2)	(3)	(4)
log (GHGpk) × log (GDPpc)	0.176***	0.175***	0.213***	0.214***
	(0.014)	(0.015)	(0.017)	(0.018)
Observations	12532	12532	11440	11440
Adjusted R^2	0.693	0.722	0.694	0.724
Country FE	Y	-	Y	-
Product FE	Y	-	Y	-
Year FE	Y	-	Y	-
Country-Year FE	-	Y	-	Y
Product-Year FE	-	Y	-	Y

Notes: * / ** / *** denotes significance at the 10 / 5 / 1 percent level. Regressions clustered at the country and food product level. Table shows estimates of parameter $\tilde{\delta}$ in equation (1). Columns (3) and (4) exclude meat products from the sample, including beef, lamb and mutton, pig meat and poultry meat.. Data includes 2000, 2010 and 2020.

positive correlation between income elasticities and GHG emissions per capita.

Our model in Section 3 captures the influence of non-homothetic preferences on GHG emissions.

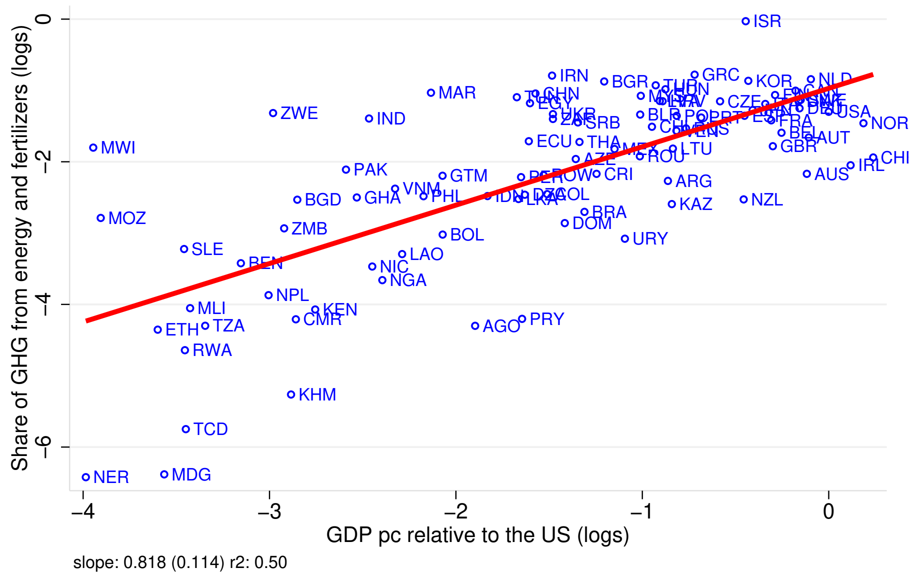
Figure 3: Income Elasticities and GHG emissions per calorie



Notes: Each point in the figure shows the point-estimate from the reduced-form estimates of income elasticity based on equation (1), δ_k. Error bars show 95% confidence intervals. The linear relation shown the best linear fit, weighting for total calories consumed from the product at the global level.

Household Level Estimates. Appendix OB presents analogous estimates of the correlation between income elasticities by food product and the CO2 emissions per product using house-

Figure 4: GHG emissions from Energy and Fertilizers and GDP per capita



Notes: This figure shows the log of GHG emissions from the use of fertilizers and energy in farm production relative total GHG emissions from food production at the country level against log of GDP per capita. Best linear fit shown in red.

hold level data from Brazil. Our qualitative findings are the similar there: Food products with higher income elasticity are more harmful for the environment and the correlation persists after controlling for a host of fixed effects, proxies for food prices or excluding meat products.

Empirical Pattern 4. GHG emissions from the use of modern agricultural technologies increase with GDP per capita. We now turn to the environmental implication of agricultural modernization. This mechanism operates *within* food products and arises in agricultural supply: richer countries have greater use of modern, input-intensive agricultural technologies (such as fertilizers and farm machinery) for a given crop, which are associated with higher levels of GHG emissions.[9] We provide evidence of this mechanism in Figure 4: GHG emissions from fertilizer and energy use per unit of total emissions from agriculture increases with GDP per capita.[10] Our model incorporates the influence of technological choices on GHG emissions.

[9]The process of intensification of agriculture is widely documented in the macro-development literature. See, for example, Donovan (2021), Farrokhi and Pellegrina (2023), and Restuccia et al. (2008).

[10]This correlation may however be influenced by varying compositions of crops (each of which each have different fertilizer intensities) produced as countries develop. Focusing on *within-crop* variation only, Appendix Figure O.3 shows that the amount of fertilizer use per unit of land is markedly increasing with GDP per capita. This suggests that even for the same crop, richer countries use more fertilizer-intense technologies.

3 Model

This section develops a global, quantitative general equilibrium that features a rich structure in agricultural consumption and production. On the demand side, consumers have non-homothetic CES preferences for different agricultural goods, which incorporates the process of nutrition transition in the economy. On the supply side, agricultural producers can choose whether to employ a traditional, labor intensive technology or a modern, labor saving one, each with different intensities of GHG emissions, which allows for the process of agricultural modernization in the economy. After presenting the model, we discuss the GHG emissions in Section 3.3, the income elasticities in Section 3.4, and derive an analytical expression for the impact of economic development on agricultural GHG emissions in Section 3.5. All derivations are included in Appendix OC.

3.1 Model Environment

We consider a global economy consisting of many countries, indexed by i or $j \in \mathcal{I}$, each of which is endowed with labor N_i and land L_i. The economy has many sectors $s \in \mathcal{S}$. Each sector has multiple goods, indexed by $k \in \mathcal{K}_s$, where $\mathcal{K}_s$ is the set of goods that belong to sector s and $\mathcal{K} \equiv \{\mathcal{K}_s\}_{s\in\mathcal{S}}$. For example, within the agricultural sector, $s = A$, each good represents different food products, such as meat, corn, and rice. Each country i produces a unique variety of good k.

Consumption and Trade. Each country i has a representative consumer who has nested non-homothetic CES preferences with a three tier structure.[11] In the upper tier, utility U_i is composed of sectoral goods $\tilde{C}_{i,s}$:

$$U_i = \left[\sum_{s\in\mathcal{S}} \left(\tilde{a}_{i,s}\right)^{\frac{1}{\sigma}} \tilde{C}_{i,s}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}. \tag{2}$$

In the middle tier, sectoral goods $\tilde{C}_{i,s}$ are composed of multiple goods $C_{i,k}$:

$$\tilde{C}_{i,s} = \left[\sum_{k\in\mathcal{K}_s} \left(a_{i,k}\right)^{\frac{1}{\varsigma}} \left(U_i^{\epsilon_k}\right)^{\frac{1}{\varsigma}} \left(C_{i,k}\right)^{\frac{\varsigma-1}{\varsigma}}\right]^{\frac{\varsigma}{\varsigma-1}}. \tag{3}$$

[11] See Duernecker et al. (2024) and Hoelzlein (2023) for recent applications of the nested non-homothetic CES preferences.

In the agricultural sector, these goods correspond to food products. In the lower tier, goods $C_{i,k}$ are composed of multiple varieties of goods $c_{ji,k}$

$$C_{i,k} = \left[\sum_{j\in\mathcal{I}} (a_{ji,k})^{\frac{1}{\eta}} (c_{ji,k})^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}. \tag{4}$$

Each country j produces a different variety of the good. Here, $\tilde{a}_{i,s}$, $a_{i,k}$ and $a_{ji,k}$ are intrinsic preference shifters for the upper, the middle and the lower tiers respectively, σ is the elasticity of substitution between sectors, ς is the elasticity of substitution between goods of each sector, and η is the elasticity of substitution between varieties of each good.[12] Non-homotheticity arises at the sectoral s and good k level due to the endogenous preference weights for each good, $U_i^{\epsilon_k}$, with the parameter ϵ_k controlling the income elasticity of good k. At the upper tier, sectors inherit non-homotheticity from the goods, but at the lower-tier, varieties remain homothetic.[13]

The representative consumer chooses consumption, $c_{ji,k}$, to maximize utility, U_i, subject to the budget constraint

$$\sum_{s\in\mathcal{S}} \sum_{k\in\mathcal{K}_s} \sum_{j\in\mathcal{I}} p_{ji,k} c_{ji,k} = E_i \tag{5}$$

where E_i is total income. Appendix OC.1 shows that this preference structure implies that for destination country i, the share of the expenditure on the variety of origin country j—i.e., the trade share—is

$$\beta_{ji,k} \equiv \frac{p_{ji,k} c_{ji,k}}{p_{i,k} C_{i,k}} = \frac{a_{ji,k} p_{ji,k}^{1-\eta}}{p_{i,k}^{1-\eta}}, \tag{6}$$

that the share of on goods k from sector $s(k)$ is

$$\beta_{i,k} \equiv \frac{p_{i,k} C_{i,k}}{\tilde{p}_{i,s(k)} \tilde{C}_{i,s(k)}} = \frac{a_{i,k} U_i^{\epsilon_k} p_{i,k}^{1-\varsigma}}{\tilde{p}_{i,s(k)}^{1-\varsigma}} \tag{7}$$

and that the share of expenditure on sectoral goods s is

$$\tilde{\beta}_{i,s} \equiv \frac{\tilde{p}_{i,s} \tilde{C}_{i,s}}{E_i} = \frac{\tilde{a}_{i,s} \tilde{p}_{i,s}^{1-\sigma}}{P_i^{1-\sigma}}. \tag{8}$$

Here, $p_{ji,k}$ is the price of the variety of good k from country j sold in i. Price indexes are

[12] We could normalize $a_{i,k}$ and $\tilde{a}_{i,s}$ to 1 w.l.o.g.. For the calibration and counterfactuals of the model, however, it is useful to keep these preference shifters separate. Note that this implies a normalization of $a_{i,k}$ and $a_{ji,k}$ is then required in each nest.

[13] *Not* having endogenous weights at the sectoral is w.l.o.g., and is equivalent to a normalization (see Appendix OC.3).

given by

$$p_{i,k}^{1-\eta} \equiv \sum_{j\in\mathcal{I}} a_{ji,k} p_{ji,k}^{1-\eta}, \qquad \tilde{p}_{i,s}^{1-\varsigma} \equiv \sum_{k\in\mathcal{K}_s} a_{i,k} U_i^{\epsilon_k} p_{i,k}^{1-\varsigma}, \quad \text{and} \quad P_i^{1-\sigma} \equiv \sum_{s\in\mathcal{S}} \tilde{a}_{i,s} \tilde{p}_{i,s}^{1-\sigma}, \tag{9}$$

where $p_{ji,k}$ is the price of variety from country j sold in country i of good k.

With this preference structure, the indirect utility per capita of the representative consumer is solved implicitly by[14]

$$U_i = \frac{E_i/N_i}{P_i} \tag{10}$$

where N_i is the population of country i.

Agricultural Production. The land endowment L_i in each country is split into multiple fields L_i^f, such that $\sum_{f\in\mathcal{F}_i} L_i^f = L_i$, where $\mathcal{F}_i$ is the set of fields that belong to country i. Each field has a continuum of plots ℓ. In each plot, agricultural producers choose which crop $k \in \mathcal{K}_A$ to produce, and with which technology τ to produce that crop. The production technology is

$$q_{i,k\tau}^f(\ell) = \left(z_{i,k\tau}^f(\ell)\right)^{\gamma_{k\tau}^L} \left(N_{i,k\tau}^f(\ell)\right)^{\gamma_{k\tau}^N} \left(\prod_{k'\in\mathcal{K}} \left(M_{i,k'k\tau}(\ell)\right)^{\lambda_{k'k}}\right)^{\gamma_{k\tau}^M},$$

where $q_{i,k\tau}^f(\ell)$ is output in units of calories, $z_{i,k\tau}^f(\ell)$ is an idiosyncratic productivity shock, $N_{i,k\tau}^f(\ell)$ is use of labor, and $M_{i,k'k\tau}(\ell)$ is the use of the composite good k' as an input for production in k. The cost share of land, labor and intermediate inputs are $\gamma_{k\tau}^L$, $\gamma_{k\tau}^N$, and $\gamma_{k\tau}^M$ and satisfy $\gamma_{k\tau}^L + \gamma_{k\tau}^N + \gamma_{k\tau}^M = 1$ and $\gamma_{k\tau}^L, \gamma_{k\tau}^N, \gamma_{k\tau}^M \geq 0$. There are two technologies available for production: (i) a modern, input intensive ($\tau = 1$ and $\gamma_{k1}^M > 0$) and (ii) a traditional, labor intensive ($\tau = 0$ and $\gamma_{k0}^M = 0$). $\lambda_{k'k}$ is the share of inputs from sector k' used in the production of k.

Agricultural producers select the crop-technology pair that maximizes the return to land in each plot ℓ, $\max z_{i,k\tau}^f(\ell)\, h_{i,k\tau}^f$ for all (k,τ), where $h_{i,k\tau}$ is the return to an efficiency unit of land

$$h_{i,k\tau} = p_{i,k}^F \left(\frac{w_i}{p_{i,k}^F}\right)^{-\frac{\gamma_{k\tau}^N}{\gamma_{k\tau}^L}} \left(\frac{\prod_{k'\in\mathcal{K}} p_{i,k'}^{\lambda_{k'k}}}{p_{i,k}^F}\right)^{-\frac{\gamma_{k\tau}^M}{\gamma_{k\tau}^L}}, \tag{11}$$

and w_i is the wage of workers.

Following Farrokhi and Pellegrina (2023), we assume that $z_{i,k\tau}^f(\ell)$ is drawn from a generalized Fréchet distribution with productivity shifters $T_{i,k\tau}^f$ and dispersion parameters θ_1 for

[14] Implicit because P_i is a function of U_i through equation (9).

the draws of crop productivity and θ_2 for the draws of technology. With this assumption, the fraction of the land in field f allocated to crop k is

$$\alpha^f_{i,k} = \frac{\left(H^f_{i,k}\right)^{\theta_1}}{\sum_{k\in\mathcal{K}_A}\left(H^f_{i,k}\right)^{\theta_1}}, \tag{12}$$

and the share of crop k allocated to technology τ in that field is

$$\alpha^f_{i,k\tau} = \frac{\left(T^f_{i,k\tau}h_{i,k\tau}\right)^{\theta_2}}{\left(H^f_{i,k}\right)^{\theta_2}}, \tag{13}$$

where $H^f_{i,k}$ is the average return of land in crop k

$$H^f_{i,k} = \left(\sum_{\tau\in\{0,1\}}\left(T^f_{i,k\tau}h_{i,k\tau}\right)^{\theta_2}\right)^{\frac{1}{\theta_2}}. \tag{14}$$

One can show that the total quantity (in units of calories) of crop k in field f and technology τ is

$$Q^f_{i,k\tau} = L^f_i\left(\gamma^L_{k\tau}\right)^{-1}\frac{h_{i,k\tau}}{p^F_{i,k}}T^f_{i,k\tau}\left(\alpha^f_{i,k}\right)^{\frac{\theta_1-1}{\theta_1}}\left(\alpha^f_{i,k\tau}\right)^{\frac{\theta_2-1}{\theta_2}}. \tag{15}$$

Total sales at the field level is given by

$$Y^f_{i,k\tau} = p^F_{i,k}Q^f_{i,k\tau}, \tag{16}$$

aggregate revenues of country i using technology τ by

$$Y_{i,k\tau} = \sum_{f\in\mathcal{F}_i}Y^f_{i,k\tau}, \tag{17}$$

and aggregate revenues of a country in agricultural good k is

$$Y_{i,k} = \sum_{\tau\in\{0,1\}}Y_{i,k\tau}. \tag{18}$$

Non-Agricultural Production. Non-agricultural firms produce goods with labor. Perfect competition ensures that

$$p^F_{i,k} = \frac{w_i}{T_{i,k}} \text{ for } k\in\{\mathcal{K}_s\}_{s\neq A}, \tag{19}$$

where $T_{i,k}$ is the total factor productivity.

Geography. To move goods from location i to j, there is an iceberg trade cost $d_{ji,k}$ that satisfies $d_{ji,k} > 1$ for $j \neq i$ and $d_{ji,k} = 1$ for $j = i$. Let $p^F_{i,k}$ be the producer price at location i, i.e., the farm-gate price for agricultural producers. $p_{ji,k}$ is therefore

$$p_{ji,k} = d_{ji,k} p^F_{i,k}. \tag{20}$$

3.2 General Equilibrium

We now establish the equations to define the general equilibrium of the model. First, total expenditure of the representative household reflects earnings from land and labor

$$E_i = w_i N_i + \sum_{k \in \mathcal{K}_A} \sum_{\tau \in \{0,1\}} \gamma^L_{k\tau} Y_{i,k\tau}. \tag{21}$$

Second, expenditure of country i on goods $k \in \mathcal{K}$ from country j is

$$X_{ji,k} = \beta_{ji,k} \left(\tilde{\beta}_{i,k} \beta_{i,s(k)} E_i + \sum_{\tau \in \{0,1\}} \sum_{k' \in \mathcal{K}_A} \lambda_{kk'} \gamma^M_{k'\tau} Y_{i,k'\tau} \right). \tag{22}$$

Third, total revenues equal total sales

$$Y_{i,k} = \sum_{j \in \mathcal{I}} X_{ij,k} \text{ for all } k \in \mathcal{K}. \tag{23}$$

Fourth, trade must balance

$$\sum_{k \in \mathcal{K}} \sum_{j \in \mathcal{I}} X_{ji,k} = \sum_{k \in \mathcal{K}} \sum_{j \in \mathcal{I}} X_{ij,k}. \tag{24}$$

Fifth, labor market clears

$$w_i N_i = \sum_{k \in \mathcal{K}_{NA}} Y_{i,k} + \sum_{k \in \mathcal{K}_A} \sum_{\tau \in \{0,1\}} \gamma^N_{i,k\tau} Y_{i,k\tau}. \tag{25}$$

Definition 1. (*General Equilibrium*) Given supply side parameters $\Gamma_S \equiv \{\lambda_{i,k'k},\ \gamma^L_{k\tau},\ \gamma^N_{k\tau},\ \gamma^M_{k\tau},\ T_{i,k},\ T^f_{i,k\tau},\ L^f_i,\ N_i\}$, demand side parameters $\Gamma_D \equiv \{a_{ij,k},\ a_{i,k}\ ,\eta\ ,\varsigma\ ,\sigma\ ,\epsilon_k\}$, and geography $\{d_{ij,k}\}$, a general equilibrium is a set of wages and producer prices $\{w_i, p^F_{i,k}\}$ such that: (i) consumers choices satisfy (6)-(9), (ii) agricultural producers choices satisfy (11)-(15), (iii) non-agricultural producers satisfy (19), (iii) non-arbitrage across locations holds (20), (iv) total sales and expenditure satisfy (18) and (21)-(23), (v) trade must balance (24) and (vi) labor markets clear (25).

3.3 Agricultural GHG Emissions

We break down the GHG emissions from agriculture into (i) the emissions from food production and (ii) the emissions from food transportation, akin to Shapiro (2016). First, production in country i generates GHG emissions, G_i^P, as follows

$$G_i^P = \sum_{k\in\mathcal{K}_A} \sum_{\tau\in\{0,1\}} \varphi_{k\tau}^P Q_{i,k\tau} \tag{26}$$

where $Q_{i,k\tau} \equiv \sum_{f\in\mathcal{F}_i} Q_{i,k\tau}^f$ is the total calories of good k produced using technology τ in country i. $\varphi_{k\tau}^P$ is the GHG emission rate by kcal from the production of agricultural good k using technology τ. We model emissions this way due to its simplicity and versatility. The parameter $\varphi_{k\tau}^P$ is a reduced-form measure capturing all sources of emissions tied to the production of a single calorie. These emissions can stem from input use that we explicitly model, such as the fertilizers and machines, or from inputs we do not model, such as energy usage and land use change. Also, our formulation allows GHG emissions to come from the production process itself, such as the release of methane from cattle ranching. With this formulation, our model captures the GHG emissions due to relocations *between* crops with different emission rates, as well as due to relocations *within* product related to technology adoption.[15]

Second, food transportation generates global GHG emissions as follows

$$G^T = \varphi^T \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{I}} \sum_{k\in\mathcal{K}_A} \text{dist}_{ij} \cdot \text{weight}_k \cdot c_{ij,k}, \tag{27}$$

where $c_{ij,k}$ is the calories consumed of good k, weight_k is a term that converts calories to weight, dist_{ij} is the distance between countries i and j , and φ^T is the GHG emissions (in kg of CO2 equivalent) per km-kg of food transported. This equation captures the role of long-distance transportation between countries in generating GHG emissions. Moreover, it

[15] Our approach assumes the contribution to emissions of each source per unit produced is constant, for a given product and technology. An alternative is to model the usage of each of these components explicitly, and directly associate the emissions to each source. The trade-off is that this requires taking a stance on the relative importance of emissions from the use of specific intermediate inputs versus the emissions that are independent from the use of such inputs, as well as building a modelling structure and collecting data on these different sources of emissions.

captures differences in GHG emissions across food products by unit of calorie, since different food products have different weights per calorie.

3.4 Income Elasticities in Nested Non-Homothetic CES

In the model presented in the preceding section, the elasticity of the expenditure share of good k within the sector $s(k)$, $\beta_{i,k}$, with respect to income, E_i (holding all variety prices fixed), is

$$\frac{\partial \ln \beta_{i,k}}{\partial \ln E_i} = \frac{1-\varsigma}{1-\varsigma+\bar{\epsilon}_i} \cdot \left(\epsilon_k - \tilde{\epsilon}_{i,s(k)}\right) \tag{28}$$

where $\tilde{\epsilon}_{i,s} \equiv \sum_{k\in\mathcal{K}_s} \beta_{i,k}\epsilon_k$ and $\bar{\epsilon}_i \equiv \sum_{s\in\mathcal{S}} \tilde{\beta}_{i,s}\tilde{\epsilon}_{i,s}$ are country i expenditure-weighted average of the income elasticity parameters, ϵ_k, at the sectoral and aggregate levels, respectively. Notice that the income elasticities in non-homothetic CES models are not structural parameters, rather they depend on consumption shares through the averages $\tilde{\epsilon}_{i,s}$ and $\bar{\epsilon}_i$, which themselves depend on prices and utility. However, the ranking of the income elasticity magnitudes within a sector are still controlled by the parameters ϵ_k, independent of the elasticities of substitution, which makes these preferences appealing. Specifically, assuming $\frac{1-\varsigma}{1-\varsigma+\bar{\epsilon}_i} > 0$, for any two products k, k' in the same sector, equation (28) implies

$$\epsilon_k \geq \epsilon_{k'} \quad \Longleftrightarrow \quad \frac{\partial \ln \beta_{i,k}}{\partial \ln E_i} \geq \frac{\partial \ln \beta_{i,k'}}{\partial \ln E_i}$$

with the left inequality strict if the right inequality is strict. Products with a greater value of ϵ_k have a greater income elasticity, for products in the same sector and country, i. The right inequality is reversed if $\frac{1-\varsigma}{1-\varsigma+\bar{\epsilon}_i} < 0$. Insight into the dependence in equation (28) of the income elasticity on the remaining parameters of the model can be had by looking at its derivation. Using equation (7),

$$\frac{\partial \ln \beta_{i,k}}{\partial \ln E_i} = \epsilon_k \underbrace{\left(1 - \frac{\partial \ln P_i}{\partial \ln E_i}\right)}_{=\frac{\partial \ln U_i}{\partial \ln E_i},\text{ using eq (10)}} - (1-\varsigma)\,\frac{\partial \ln \tilde{p}_{i,s(k)}}{\partial \ln E_i} \tag{29}$$

A change in expenditure causes utility to change, which affects the consumption expenditure share of product k via two channels. The first is the direct effect of the change in utility, which causes the preference weight given to product k to change due to preferences being non-homothetic. This is modulated by the parameter ϵ_k and is the first term in equation (29). Utility is equal to real expenditure, $U_i = (E_i/N_i)/P_i$, thus this channel incorporates the resulting change in the overall price index P_i due to the non-homothetic adjustment of the overall consumption basket as utility changes. The second channel, reflected by the second term in equation (29), arises due to the non-homothetic adjustment of the sectoral consumption basket, causing the sectoral price index, $\tilde{p}_{i,s(k)}$, to change. The change in these price indices induces a substitution effect, which is modulated by the elasticities of substitution, ς and σ. Hence, the dependence of the income elasticity on these parameters.

Similarly to the good-level case, the elasticity of the expenditure share of sector s, $\tilde{\beta}_{i,s}$, with respect to income, E_i, for households in country i, is given by

$$\frac{\partial \ln \tilde{\beta}_{i,s}}{\partial \ln E_i} = \frac{1-\sigma}{1-\varsigma+\bar{\epsilon}_i} \cdot \left(\tilde{\epsilon}_{i,s} - \bar{\epsilon}_i\right) \tag{30}$$

The ranking of these sectoral income elasticities are determined by the average of the income elasticities across the sector's constituent products, $\tilde{\epsilon}_{is}$. Specifically, assuming $\frac{1-\sigma}{1-\varsigma+\bar{\epsilon}_i} > 0$, for any two sectors s, s'

$$\tilde{\epsilon}_{i,s} \geq \tilde{\epsilon}_{i,s'} \quad \iff \quad \frac{\partial \ln \tilde{\beta}_{i,s}}{\partial \ln E_i} \geq \frac{\partial \ln \tilde{\beta}_{i,s'}}{\partial \ln E_i}$$

with the left inequality strict if the right inequality is strict. The right inequality is reversed if $\frac{1-\sigma}{1-\varsigma+\bar{\epsilon}_i} < 0$. That is, the sectors inherit their non-homotheticity from the product-level income elasticity parameters, ϵ_k.

The elasticity of expenditure on a product, k, with respect to income in country i is

$$\frac{\partial \ln \left(p_{i,k} C_{i,k}\right)}{\partial \ln E_i} = \underbrace{\frac{\partial \ln \beta_{i,k}}{\partial \ln E_i}}_{\text{Reallocation between } k \text{ within } s(k)} + \underbrace{\frac{\partial \ln \tilde{\beta}_{i,s(k)}}{\partial \ln E_i}}_{\text{Reallocation between } s} + \underbrace{1}_{\text{Scale}} \tag{31}$$

using $p_{i,k} C_{i,k} = \beta_{i,k} \tilde{\beta}_{i,s(k)} E_i$. This elasticity captures both reallocation in expenditure across products k within the sector $s(k)$, $\frac{\partial \ln \beta_{i,k}}{\partial \ln E_i}$, reallocation between sectors, $\frac{\partial \ln \tilde{\beta}_{i,s(k)}}{\partial \ln E_i}$, and the overall scale effect from having greater income, given by the last term, 1.

The reduced form income elasticities by product, δ_k, estimated in equation (1) correspond to

$$\delta_k = \mathbb{E}_{i|k}\left[\frac{\partial \ln \left(p_{i,k} C_{i,k}\right)}{\partial \ln E_i}\right] \tag{32}$$

The expectation over i (with k fixed), $\mathbb{E}_{i|k}$, is present due to the regression taking an expenditure-weighted average of the income elasticities across countries. δ_k is the effect of an increase in income, E_i on the total expenditure on product k, $p_{i,k} C_{i,k}$, averaged across countries.

The reduced form estimation permits one to identify $K_s - 2$ of the income elasticity parameters ϵ_k for each sector (as observed in Comin et al., 2021 for non-nested NHCES).

This can be seen by inserting equations (28) and (31) into equation (32), giving

$$\frac{\delta_k - \delta_{k'}}{\delta_k - \delta_{k''}} = \frac{\epsilon_k - \epsilon_{k'}}{\epsilon_k - \epsilon_{k''}} \tag{33}$$

for products k, k', k'' all in the same sector.

3.5 Economic Development and GHG Emissions from Food Production

To gain intuition on the model mechanisms relating the change in GHG emissions from food production to economic development, we provide an analytical decomposition up to first order in this section. Modeling economic development as an increase in domestic TFP in the non-agricultural sector, $T_{i,NA}$, the effect on domestic agricultural emissions from production, G_i^P, is

$$\begin{aligned}
\frac{\mathrm{d}\ln G_i^P}{\mathrm{d}\ln T_{i,NA}} = & \sum_{k\in\mathcal{K}_A}\sum_{\tau\in\{0,1\}} \frac{\varphi_{k\tau}^P Q_{i,k\tau}}{G_i^P} \cdot \frac{\partial \ln \frac{Q_{i,k\tau}}{Q_{i,k}}}{\partial \ln w_i} \cdot \frac{\mathrm{d}\ln w_i}{\mathrm{d}\ln T_{i,NA}} \quad \text{Agricultural modernization} \\
& + \sum_{j\in\mathcal{I}}\sum_{k\in\mathcal{K}_A} \frac{X_{ij,k}}{Y_{i,k}} \cdot \frac{\sum_{\tau\in\{0,1\}} \varphi_{k\tau}^P Q_{i,k\tau}}{G_i^P} \cdot \frac{\partial \ln \beta_{j,k}}{\partial \ln E_j} \cdot \frac{\mathrm{d}\ln E_j}{\mathrm{d}\ln T_{i,NA}} \quad \text{Nutrition transition} \\
& + \sum_{j\in\mathcal{I}} \frac{\sum_{k\in\mathcal{K}_A} \frac{X_{ij,k}}{Y_{i,k}} \sum_{\tau\in\{0,1\}} \varphi_{k\tau}^P Q_{i,k\tau}}{G_i^P} \cdot \frac{\partial \ln\left(\tilde{p}_{j,A}\tilde{C}_{j,A}\right)}{\partial \ln E_j} \cdot \frac{\mathrm{d}\ln E_j}{\mathrm{d}\ln T_{i,NA}} \quad \text{Scale effect} \\
& + \sum_{k\in\mathcal{K}_A}\sum_{\tau\in\{0,1\}} \frac{\varphi_{k\tau}^P Q_{i,k\tau}}{G_i^P} \cdot \frac{\partial \ln Q_{i,k\tau}}{\partial \ln \mathbf{p}'} \cdot \frac{\mathrm{d}\ln \mathbf{p}}{\mathrm{d}\ln T_{i,NA}} \quad \text{Price effect}
\end{aligned} \tag{34}$$

where $Q_{i,k} \equiv \sum_{\tau\in\{0,1\}} Q_{i,k\tau}$ is total calories from production of crop k in country i. Following the TFP shock, economic development occurs in location i if the wage w_i and income E_i rise, $\frac{\mathrm{d}\ln w_i}{\mathrm{d}\ln T_{i,NA}} > 0$, $\frac{\mathrm{d}\ln E_j}{\mathrm{d}\ln T_{i,NA}} > 0$, which is the typical case and what we will assume for exposition.

The negative environmental consequences of agricultural modernization manifest in the first term: if, as the wage rises, production shifts to technologies with a greater share of emissions. That is, $\frac{\partial \ln \frac{Q_{i,k\tau}}{Q_{i,k}}}{\partial \ln w_i}$ is positive for the technology with greater emissions, $\frac{\varphi_{k\tau} Q_{i,k\tau}^C}{G_i}$. This is the empirically relevant case in the model because the modern technology has greater emissions and is labor saving, $\frac{\gamma_{k1}^N}{\gamma_{k1}^L} < \frac{\gamma_{k0}^N}{\gamma_{k0}^L}$ (i.e. labor per unit of land), so producers switch to this technology as wages rise. This implication can be seen cleanly in the case where there is only a single field in country i, $|\mathcal{F}_i| = 1$, in the model

$$\frac{\partial \ln \frac{Q_{i,k\tau}}{Q_{i,k}}}{\partial \ln w_i} = \theta_2 \frac{Q_{i,k,1-\tau}}{Q_{i,k}} \left(\frac{\gamma_{k,1-\tau}^N}{\gamma_{k,1-\tau}^L} - \frac{\gamma_{k\tau}^N}{\gamma_{k\tau}^L} \right) \tag{35}$$

which is positive for the modern technology, $\tau = 1$, and negative for the traditional, $\tau = 0$.

The negative environmental consequences of the nutrition transition manifest in the second term: if, as income rises, consumption shifts to products with a greater share of emissions. That is, $\frac{X_{ii,k}}{Y_{i,k}} \frac{\partial \ln \beta_{i,k}}{\partial \ln E_i}$ is positive for the goods with greater emissions (combined across traditional and modern), $\frac{\sum_{\tau \in \{0,1\}} \varphi^P_{k\tau} Q_{i,k\tau}}{G_i}$. Ignoring the effect of the domestic trade share, $\frac{X_{ii,k}}{Y_{i,k}}$, for the moment, this is the empirically relevant case because goods with greater values of ϵ_k, and therefore greater income elasticities, $\frac{\partial \ln \beta_{j,k}}{\partial \ln E_j}$, by equation (28), have greater emissions. The presence of the domestic trade share can attenuate the nutrition transition if high emission products have have low domestic trade shares, meaning these products are sourced from abroad. Moreover, incomes in other countries $j \neq i$ may not necessarily rise following the domestic TFP increase, $\frac{\mathrm{d} \ln E_j}{\mathrm{d} \ln T_{i,NA}} \gtrless 0$; any fall in foreign incomes will further attenuate the nutrition transition as the composition of foreign consumption shifts to less emitting products.

The third term reflects a scale effect: if global expenditure on the domestic agricultural sector rises following the TFP shock, then domestic agricultural emissions increase mechanically, simply because more agricultural products are being produced. The income elasticity of the agricultural sector as a whole is positive in the empirically relevant case, $\frac{\partial \ln\left(\tilde{p}_{j,A} \tilde{C}_{j,A}\right)}{\partial \ln E_j} > 0$, so the scale effect is positive assuming any fall in foreign income following the domestic TFP shock is not too great.

The final term reflects the effect of the endogenous price response on agricultural output following the TFP shock. We use the notation $\mathbf{p} = \left\{p^F_{i,k}\right\}_{i \in \mathcal{I}, k \in \mathcal{K}}$, with an inner product between the two derivatives involving the price. Agricultural modernization and the nutrition transition are income effect phenomena. Therefore, any effect on emissions through a change in prices is a distinct mechanism.

4 Quantifying the Model

We present our quantification in Section 4.1 and results, including model fit, in Section 4.2. Table 2 offers a summary of our calibrated and estimated parameters.

4.1 Quantification

The quantification of our model follows a three step procedure. First, we estimate the income elasticity parameters by food product ($\{\epsilon_k\}_{k \in \mathcal{K}_A}$) and set the elasticities of substitution in consumption $(\eta, \varsigma, \sigma)$ equal to values in the literature. Second, we calibrate the productivity shifters (T_{ik} and $T^f_{ik\tau}$), the cost share parameters ($\gamma^L_{k\tau}$, $\gamma^N_{k\tau}$, $\gamma^M_{k\tau}$, and $\lambda_{k'k}$), and the preference

Table 2: Summary of Parameter Values and Sources

Parameter	Description	Source	Value
Demand-side			
η	Elasticity of subst. between varieties	Simonovska and Waugh (2014)	4
ς	Elasticity of subst. between goods	Sotelo (2020) and Farrokhi and Pellegrina (2023)	3
σ	Elasticities of subst. between sectors	Comin et al. (2021)	0.5
ϵ_k	Income elasticities for each goods	Methology in Section 3.4	-
$a_{ji,k}d_{ji,k}^{1-\eta}$	Demand shifters and trade costs	Residuals from gravity equations	-
$a_{i,k}$ and $\tilde{a}_{i,s}$	Demand shifters of goods and sectors	Good- and sector-level expenditure shares	-
Supply-side			
θ_1	Productivity dispersion between crops	Farrokhi and Pellegrina (2023)	1.5
θ_2	Productivity dispersion between tech.	Farrokhi and Pellegrina (2023)	4.5
$\gamma_{k\tau}^N, \gamma_{k\tau}^L, \gamma_k^M, \lambda_{kk'}$	Factor and intermediate input shares	USDA & Cross-country input cost share	-
$T_{i,k\tau}^f$	Productivity shifter for food products	Potential yields from FAO-GAEZ	-
$T_{i,k}$	Productivity shifter of non-agriculture	Origin FE from gravity equations	-
GHG emissions from food production $\varphi_{k\tau}^P$			
φ_k	Emissions by food product	Poore and Nemecek (2018)	-
φ_0	Global emissions from food production	EDGAR-FOOD	2.2
φ_1	Emissions of rich and poor countries	EDGAR-FOOD	6.8
GHG emissions from food transport φ^T			
φ^T	Global emissions from food transport	EDGAR-FOOD	0.08

shifters ($\tilde{a}_{i,s}$, $a_{i,k}$, and $a_{ij,k}$), while picking values for the crop-technology elasticities (θ_1 and θ_2) from the literature. Third, with the baseline model calibrated and simulated, we estimate the GHG emissions from food production per crop and technology, $\varphi_{k\tau}^{\mathrm{P}}$, and from food transport, φ^{T}.

4.1.1 Step 1: Income and Substitution Elasticities

Our method to estimate the income elasticity parameters generalizes Comin et al. (2021) to *nested* non-homothetic CES preferences and to an open-economy. As in their case, we utilize the implicit Marshallian demand for identification.[16] Specifically, the *explicit* Marshallian demand under non-homothetic CES preferences cannot be written in closed-form because of the dependence of the middle tier price indices, $\tilde{p}_{i,s}$ on utility, U_i. However, one can still derive a closed-form demand equation that depends on expenditure on a base good in place of these price indices, becoming what is referred to as the *implicit* Marshallian demand. Here, we show that one can use trade data to further substitute out the unobservable variety price indices, $p_{i,k}$, resulting in a specification that does not require any price data, while still being exact.[17] We briefly explain the estimation steps below, providing a full derivation in

[16] Alternatively, Caron and Fally (2022); Duernecker et al. (2024) use the Hicksian demand, equation (7), and the budget constraint, equation (5), or utility function, equation (2), simultaneously for identification. Estimation based on that method necessitates a constrained, non-linear least squares regression, whereas the implicit Marshallian demand permits a linear regression.

[17] Comin et al. (2021) and Caron and Fally (2022) provide approximate methods for the non-nested non-homothetic CES that do not require price data: they impose additional assumptions that are only approxi-

Appendix Section OD.1.

The first step is to use a base good $k^* \in \mathcal{K}$, which will be non-agriculture in our setting, to substitute out the upper and middle level price indices, P_i and $\tilde{p}_{i,s}$. To substitute out the overall price index, P_i, rearrange demand for the sector of the base good, equation (8), to give

$$\begin{aligned} P_i^{1-\sigma} &= \frac{\tilde{a}_{i,s(k^*)}\tilde{p}_{i,s(k^*)}^{1-\sigma}}{\tilde{\beta}_{i,s(k^*)}} \\ &= \frac{\tilde{a}_{i,s(k^*)}\left(a_{i,k^*}U_i^{\epsilon_{k^*}}p_{i,k^*}^{1-\varsigma}\right)^{\frac{1-\sigma}{1-\varsigma}}}{\tilde{\beta}_{i,s(k^*)}} \\ &= \frac{\tilde{a}_{i,s(k^*)}a_{i,k^*}^{\frac{1-\sigma}{1-\varsigma}}p_{i,k^*}^{1-\sigma}}{\tilde{\beta}_{i,s(k^*)}} \end{aligned} \tag{36}$$

The second line used equation (9) and the fact that the non-agricultural sector $s(k^*)$ has only a single product in our model, $\left|\mathcal{K}_{s(k^*)}\right| = 1$ (a sole non-agricultural composite). The third line utilized the normalization $\epsilon_{k^*} \equiv 0$ (see proposition 1 in Appendix Section OC.3).

Next, to substitute out the sectoral price indices of the other sectors, $\forall s \in \mathcal{S} \backslash s(k^*) : p_{i,s}$, rearrange demand for those sectors, equation (8),

$$\tilde{p}_{i,s}^{1-\sigma} = \frac{\tilde{\beta}_{i,s}P_i^{1-\sigma}}{\tilde{a}_{i,s}} \tag{37}$$

Equations (36) and (37) provide expressions for P_i and $\tilde{p}_{i,s}$ that, conditional the expenditure shares, $\tilde{\beta}_{i,s}$, and variety price indices, p_{i,k^*}, do not directly depend on utility.

The second step is to use the demand for varieties, equation (6), to substitute out the variety price index, that, while not directly depending on utility, is unobservable.[18] Rearranging equation (6), inserting $p_{ji,k} = p_{j,k}^F d_{ji,k}$ from equation (20), taking logs, and summing

mately true in reality. Comin et al. (2021) assume prices do not vary across different groups of consumers; Caron and Fally (2022) require proxies for crop-specific trade costs (they use standard gravity variables such as physical distance and shared language). Our method, in contrast, is exact, requiring no such additional assumptions.

[18] Costinot et al. (2016) identify variety price indices using data on production prices, combined with estimates of $a_{ji,k}\tau_{ji,k}^{1-\eta}$ from residuals in their regressions. Our method, on the other hand, for our purposes, does not need production price data.

over country i's import partners $j \in \mathcal{I}_{i,k}^{\neg 0}$, gives

$$(1-\eta)\ln p_{i,k} = \underbrace{-\frac{1}{N_{\mathcal{I}_{i,k}^{\neg 0}}}\sum_{j\in\mathcal{I}_{i,k}^{\neg 0}}\ln\beta_{ji,k}}_{\equiv \ln\hat{\beta}_{i,k}} + (1-\eta)\underbrace{\frac{1}{N_{\mathcal{I}_{i,k}^{\neg 0}}}\sum_{j\in\mathcal{I}_{i,k}^{\neg 0}}\ln p_{j,k}^{F}}_{\equiv \ln\hat{p}^{F}_{\mathcal{I}_{i,k}^{\neg 0},k}} + \underbrace{\frac{1}{N_{\mathcal{I}_{i,k}^{\neg 0}}}\sum_{j\in\mathcal{I}_{i,k}^{\neg 0}}\ln\left(a_{ji,k}d_{ji,k}^{1-\eta}\right)}_{\equiv 0} \tag{38}$$

$\mathcal{I}_{i,k}^{\neg 0}$ is the set of non-zero trade flows into location i for industry k, i.e. $\mathcal{I}_{i,k}^{\neg 0} \equiv \{j \in \mathcal{I} : \beta_{ji,k} \neq 0\}$ and $N_{\mathcal{I}_{i,k}^{\neg 0}} \equiv \left|\mathcal{I}_{i,k}^{\neg 0}\right|$ is the number of elements in this set (i.e. the number of importing partners). Summing over this set is required to avoid log of zero in the summand.

$\hat{\beta}_{i,k}$ and $\hat{p}^{F}_{\mathcal{I}_{i,k}^{\neg 0},k}$ are geometric averages of variety expenditure shares, $\beta_{ji,k}$, and production prices, $p_{j,k}^{F}$, across location i's import partners for product k. The third term in equation (38) is normalized to zero, without loss of generality.[19]

The final step is to use equations (36), (37) and (38) to substitute out $\tilde{p}_{i,s}$, P_i and $p_{i,k}$, respectively, in demand for good $k \neq k^*$, equation (7)

$$\begin{aligned}\ln\beta_{i,k} = \epsilon_k \ln\frac{E_i}{N_i} - \left(\frac{1-\varsigma}{1-\sigma}\right)\ln\tilde{\beta}_{i,s(k)} - \frac{1-\varsigma}{1-\eta}\ln\hat{\beta}_{i,k} + \frac{\epsilon_k+1-\varsigma}{1-\sigma}\ln\tilde{\beta}_{i,s(k^*)} + \frac{\epsilon_k+1-\varsigma}{1-\eta}\ln\hat{\beta}_{i,k^*} \\ + \underbrace{(1-\varsigma)\ln\hat{p}^{F}_{\mathcal{I}_{i,k}^{\neg 0},k}}_{\left\{\mathcal{I}_{i,k}^{\neg 0},k\right\}\text{ FE}} + \underbrace{(\varsigma-1-\epsilon_k)\ln\hat{p}^{F}_{\mathcal{I}_{i,k^*}^{\neg 0},k^*}}_{\left\{\mathcal{I}_{i,k^*}^{\neg 0},k\right\}\text{ FE}} + \underbrace{\ln\left(\frac{a_{i,k}\tilde{a}_{i,s(k)}^{\frac{1-\varsigma}{1-\sigma}}}{a_{i,k^*}^{\frac{\epsilon_k+(1-\varsigma)}{1-\varsigma}}\tilde{a}_{i,s(k^*)}^{\frac{\epsilon_k+(1-\varsigma)}{1-\sigma}}}\right)}_{\text{residual}}\end{aligned} \tag{39}$$

Equation (39) is the *implicit* Marshallian demand for products and form the basis of our estimation of ϵ_k for $k \neq k^*$. The dependent variable and regressors are constructed using observable per capita expenditure, E_i/N_i, and expenditure shares, $\beta_{i,k}, \tilde{\beta}_{i,s(k)}, \tilde{\beta}_{i,s(k^*)}, \hat{\beta}_{i,k}$, and $\hat{\beta}_{i,k^*}$. Importantly, because the estimation equation only depends on averages of the production prices, $\hat{p}^{F}_{\mathcal{I}_{i,k}^{\neg 0},k}$ and $\hat{p}^{F}_{\mathcal{I}_{i,k^*}^{\neg 0},k^*}$, these terms can be controlled for using appropriate fixed effects. For instance, the $\left\{\mathcal{I}_{i,k}^{\neg 0},k\right\}$ fixed effect has a dummy for the set of county-product, i,k, observations that share the same set of import partners for product k, $\mathcal{I}_{i,k}^{\neg 0}$, and share the same product, k. Thus, no price data is needed for estimation.

Not needing price data is a powerful feature of our method. This arises because the model is open-economy. Multiple countries purchase a given product from the same set of countries at the same production prices. By utilizing variation across different countries purchasing the same products, one can difference out the production price in the estimation equation. The presence of $\hat{\beta}_{i,k}$ arises because one must still adjust by the amount each country is exposed

[19]The level of $a_{ji,k}$ in each nest can be normalized — see footnote 12. This is for the same reasons as in Costinot et al., 2016, equation 12.

to each price via its imports.

The unobservable preference shifters of the middle and upper tiers of utility, $a_{i,k}$ and $\tilde{a}_{i,s}$, constitute the residual. Variation in income and expenditure shares that is orthogonal with respect to these preference shifters is therefore needed for identification. We follow the precedent in the literature that assumes the fixed effects are sufficient to account for endogeneity (Aguiar and Bils, 2015; Comin et al., 2021).

Equation (39) in principle identify all the parameters $\left\{\{\epsilon_k\}_{k\in\mathcal{K}\setminus k^*}, \eta, \varsigma, \sigma\right\}$, which can be estimated by non-linear methods. Since η, ς, and σ are often estimated in the literature, we calibrate these parameters instead, which allows us to use a simple linear regression to estimate $\{\epsilon_k\}_{k\in\mathcal{K}\setminus k^*}$. That is, for $k \in \mathcal{K}\setminus k^*$,

$$\ln\left(\beta_{i,k}\tilde{\beta}_{i,s(k)}^{\frac{1-\varsigma}{1-\sigma}}\hat{\beta}_{i,k}^{\frac{1-\varsigma}{1-\eta}}\tilde{\beta}_{i,s(k^*)}^{-\frac{1-\varsigma}{1-\sigma}}\hat{\beta}_{i,k^*}^{-\frac{1-\varsigma}{1-\eta}}\right) = \epsilon_k \ln\left(\frac{E_i}{N_i}\tilde{\beta}_{i,s(k^*)}^{\frac{1}{1-\sigma}}\hat{\beta}_{i,k^*}^{\frac{1}{1-\eta}}\right) + \underbrace{(1-\varsigma)\ln\hat{p}^F_{\mathcal{I}^{\neg 0}_{i,k},k}}_{\left\{\mathcal{I}^{\neg 0}_{i,k},k\right\}\text{ FE}}$$
$$+ \underbrace{(\varsigma - 1 - \epsilon_k)\ln\hat{p}^F_{\mathcal{I}^{\neg 0}_{i,k^*},k^*}}_{\left\{\mathcal{I}^{\neg 0}_{i,k^*},k\right\}\text{ FE}} + \underbrace{\ln\left(\frac{a_{i,k}\tilde{a}_{i,s(k)}^{\frac{1-\varsigma}{1-\sigma}}}{a_{i,k^*}^{\frac{\epsilon_k+(1-\varsigma)}{1-\varsigma}}\tilde{a}_{i,s(k^*)}^{\frac{\epsilon_k+(1-\varsigma)}{1-\sigma}}}\right)}_{\text{residual}} \tag{40}$$

We set the trade elasticity to $\eta = 4$ (Simonovska and Waugh, 2014), the elasticity of substitution between crops to $\varsigma = 3$, which is in between the values found in Sotelo (2020) using household-level variations and Farrokhi and Pellegrina (2023) country-level variations, and the elasticity of substitution between agriculture and non-agricultural goods to $\sigma = 0.5$ (Comin et al., 2021).

4.1.2 Step 2: Technology Parameters, Productivity Shifters and Preference Shifters

Because we follow closely the literature, this section provides a brief summary of our procedure, leaving details to Appendix OD. We set the technology and crop supply elasticities to be equal to $\theta_1 = 1.5$ and $\theta_2 = 4$, and adjust the productivity shifters for the agricultural sector ($T^f_{i,k\tau}$) based on the FAO-GAEZ data, as in Farrokhi and Pellegrina (2023). Specifically, the relative values of $T^f_{i,k\tau}/T^{f'}_{i',k\tau}$ for each technology across the world comes directly from the information provided by FAO-GAEZ. The level of $T^f_{i,k\tau}$ in traditional technology is adjusted to match the total calories produced by each food product at the global level, and the modern technology is adjusted to match exactly the share of land employed in modern technology in the United States.

We recover the amalgamation of lower tier preference shifters, $a_{ji,k}$, with international trade costs, $d_{ij,k}$, from the residuals of the variety gravity equations — i.e. $a_{ij,k}d_{ij,k}^{1-\eta}$.[20] We also recover the origin fixed effects from these gravity equations for the non-agricultural good and each intermediate input (fertilizers, machinery and pesticide), which we use to calibrate $T_{i,k}$ (up-to-normalization within each good). Middle tier preference shifters, $a_{i,k}$, match the share of calories each country consumes from each food product, and upper tier preference shifter, $\tilde{a}_{i,s}$, match the expenditure share in agricultural goods by each country (both up to a separate normalization within country).

For the cost share of inputs $\gamma_{k\tau}^{L}$, $\gamma_{k\tau}^{N}$, and $\gamma_{k\tau}^{M}$, for simplicity, we assume that the technology parameters are the same across food products. Moreover, based on the FAO-GAEZ assumptions when generating the potential yield data, we set the use of agricultural inputs in traditional technology to zero, $\gamma_{k1}^{M} = 0$. We then use data on the observed cost share of labor, land and intermediate inputs from the USA, which is a weighted average of the cost share of each input across modern and traditional technologies, together with information on total revenues from modern technologies to recover the remaining shares. Lastly, the cost share of intermediate inputs, $\lambda_{k,k'}$, comes from the USDA productivity and cost share dataset.

4.1.3 Step 3: Calibrating GHG Emissions

In this final step, after calibrating the model, we estimate the GHG emission parameters from production, $\varphi_{k\tau}^{P}$, using the minimum distance estimator and calibrate the parameter related to food transportation, φ^{T}, using data on global GHG emissions from transportation. To reduce data requirements, we assume that the GHG emissions from food production is a combination of a crop-specific component and a technology-specific component as follows, $\varphi_{k\tau}^{P} = \varphi_k \varphi_\tau$. We calibrate the value of φ_k so that the relative average emission across food products in the model matches the corresponding statistics in PN18. We then estimate φ_0 and φ_1 based on two additional statistics from EDGAR-FOOD. First, the total GHG emissions from food production in the data—which equals 4.6 Gt CO2 in 2010. Second, the ratio of total GHG emissions from food production between countries above the 75 percentile of the distribution of GDP per capita versus the emissions from countries below the 25 percentile—that ratio equals 15 percent. This second statistic provides information about the unobserved use of modern technologies across countries, which is consistent with the higher emissions from fertilizers and energy use in richer economies presented in Empirical

[20] We recall that we are only identified up-to-normalization here so we assume $\frac{1}{N_{\mathcal{I}_{i,k}^{\neg 0}}} \sum_{j \in \mathcal{I}_{i,k}^{\neg 0}} \ln \left(a_{ji,k} d_{ji,k}^{1-\eta} \right) = 0$. See 12 for details.

Pattern 4.[21]

Formally, let $\bar{m} = [m_{avg}, m_{25,75}]$ be the vector that stacks these two statistics in the data in logs, $\Sigma \equiv \{\varphi_0, \varphi_1\}$ be the vector of parameters to be estimated, and $\bar{\varphi}_k$ be the average emissions from food product k in the data relative to the average (unweighted) emissions across food products. We search for $\widehat{\Sigma}$ that satisfies

$$\widehat{\Sigma} = \arg\min \left[m\left(\Sigma\right) - \overline{m}\right]' \left[m\left(\Sigma\right) - \overline{m}\right] \text{ s.t. } \bar{\varphi}_k = \varphi_k\left(\Sigma\right)$$

where $m\left(\Sigma\right)$ are the model-implied values of $\bar{m}$ with parameters Σ, and $\varphi_k\left(\Sigma\right)$ are the model-implied values of $\bar{\varphi}_k$.

Finally, using equation (27), we calibrate φ^T to match the global emissions from the transportation of food in the data.

We find that the ratio of φ_1 to φ_0, which provides the additional GHG emissions from using modern technologies, equals 2.92 (= 6.66/2.28). Additionally, we find $\varphi^T = 0.08$, which means that transporting 1 kg of a good for 1 km produces 0.08 gCO2 emissions. For comparison, according to the International Maritime Organization Greenhouse Gas Study (IMO, 2020), the gCO2 emissions per kg-km is 0.01 via maritime routes in 2008. For other modes of transportation, such as road and air transportation, these numbers are about 10 and 100 times higher, respectively, which can explain our larger values.

4.2 Income Elasticity Estimates and Fit of the Model

4.2.1 Income Elasticities

Figure 5a presents the estimated values of the income elasticity parameters, along with 95% confidence intervals. Recall that these are not equal to the income elasticities, but they have the same ranking within sector—recall also that non-agriculture is normalized to zero. Figure 5a presents the implied income elasticity (averaged across all countries), calculated using equation (31). The ranking looks as one would expect: potatoes and rice have some of the lowest values, while berries and asparagus are on the highest ends. Meats tend to be towards the middle.

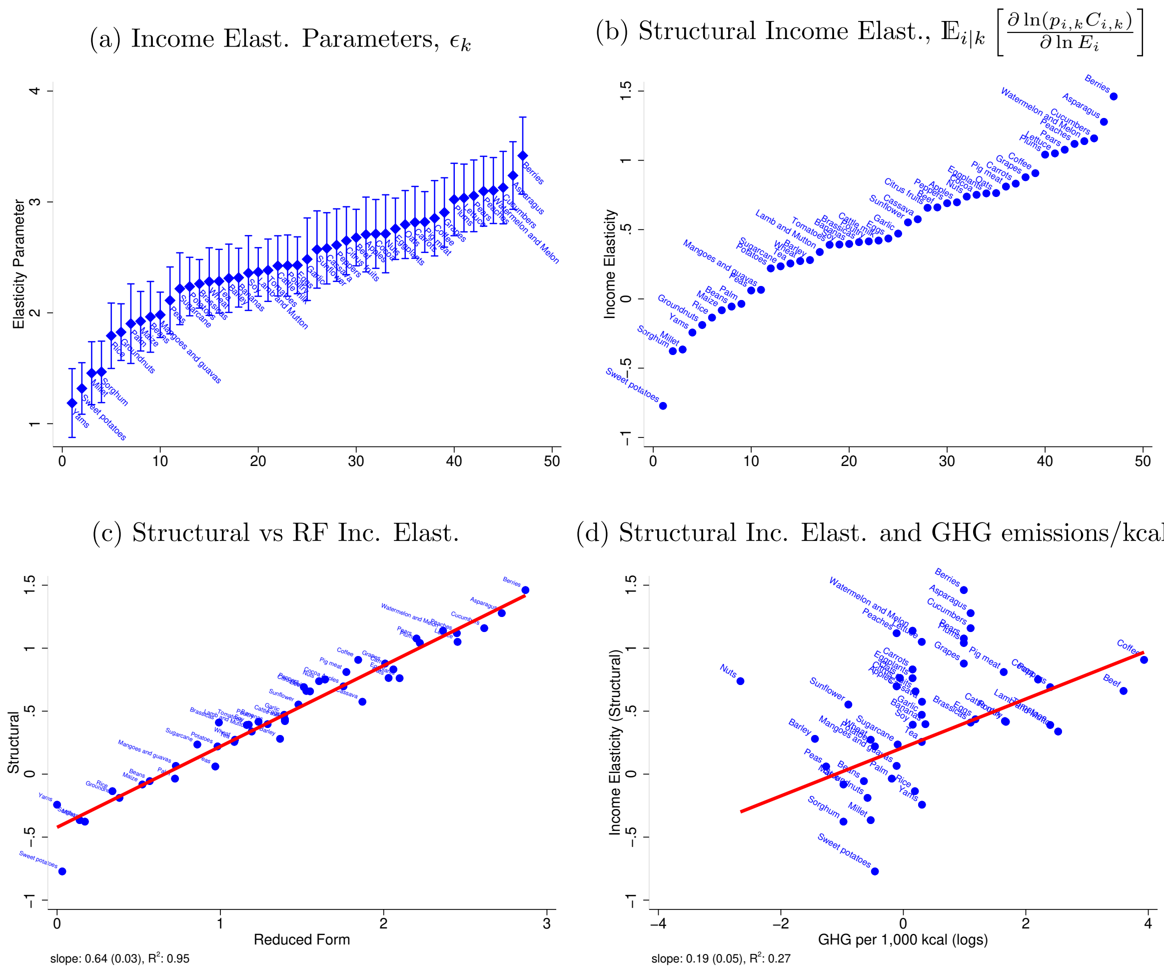
Figure 5c plots the structural income elasticity values against the corresponding reduced form in Equation (1) from Empirical Pattern 3. There is a strong relationship between the two, with slope of 0.77 and R^2 of 0.93: the structural estimation yields similar values to

[21] Notice that, if we assume that emissions between technologies are the same ($\varphi_1 = \varphi_0$), then the model-implied differences in GHG emissions across poor and rich countries are understated relative to the data, because these differences can only arise from differences in total food production and differences in food-product composition.

the reduced-form coefficients. This is reassuring: both methods make different identifying assumptions; similar results from both suggest that our results are therefore robust to both sets of assumptions.[22]

Figure 5d plots the structural income elasticities against the GHG per calorie of each product, to verify if Empirical Pattern 3 is replicated by the model. Indeed it is, with a significant positive slope.

Figure 5: Estimation of Income Elasticities and Parameters



Notes: Panel (a) shows the estimated values (with 95% confidence intervals) of ϵ_k by product. Panel (b) shows the implied income elasticities from equation (31). Panel (c) shows the relationship between the structural values of the income elasticities and the reduced form values — Equation (1). Panel (d) shows the relationship between the structural income elasticities and GHG emissions per calorie.

The income elasticity of the agricultural sector as a whole implied by our model is 0.39,

[22]The two methods assume different data-generating processes: the reduced form method assumes that any endogeneity is sufficiently controlled for using the fixed effect specification in equation (1), while the structural method correctly accounts for endogeneity assuming the residual is governed by the model of section 3.

which is in line with the results from the literature. Comin et al. (2021), for example, find an elasticity of 0.37 using cross-country data.

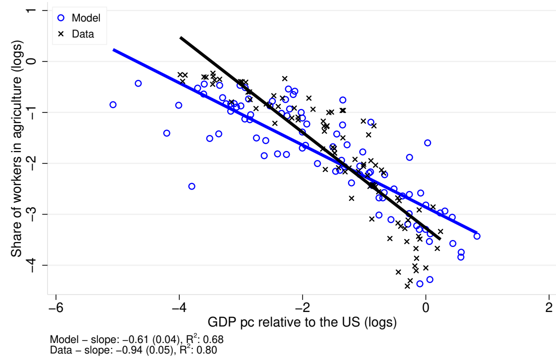
4.2.2 Fit of the Model

Figure 6 shows that the model replicates a host of key patterns in the data related to agricultural production, GHG emissions, and economic development, even though none of these empirical patterns were directly targeted in our quantification procedure.[23] Panel (a) shows that the model generates a declining share of workers in agriculture with economic development, a well-known empirical regularity from the literature (Comin et al., 2021; Herrendorf et al., 2014). In our model, this relationship is partly driven by the higher ratio of wages to intermediate input prices in richer economies, which incentivizes the adoption of modern, labor-saving agricultural technologies. Panel (b) presents an increasing cost share of inputs with economic development, a regularity emphasized in Donovan (2021), Farrokhi and Pellegrina (2023), and Restuccia et al. (2008). This pattern is a consequence of the higher use of modern technology in richer economies. (We notice that we only directly target the share of modern technology in the US; the distribution of modern technology shares across other countries is model-implied and not calibrated explicitly.) Panel (c) evaluates the model's fit regarding the share of land in modern technology. Due to limited data—few countries report detailed information on land use by technology type—the model's outcomes, nonetheless, remain consistent with observed data. Figure 6 d), e) and f) show that the model replicates the relationships observed in empirical pattern 2 between economic development and GHG emissions: food GHG emissions from food consumption increases, both in per capita and per calorie terms, and calories increase.

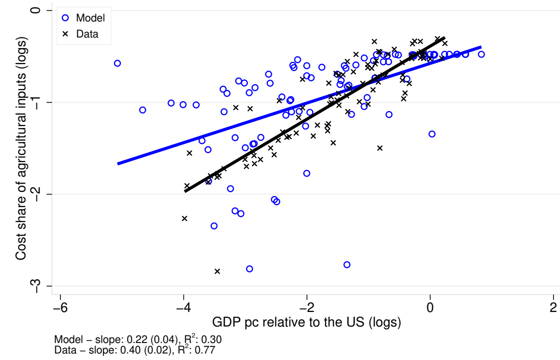
[23] While our focus is on these relationships in the data, we notice that the model fits well aggregate production by country and food product. A regression of the log of quantities in the data against the log of quantities in the model gives a slope of 0.75 and a R2 of 0.38 — see Appendix Figure O.4. That indicates that the model generates systematically more variation in specialization than in the data, particularly by producing low amounts of production for certain crops relative to the data.

Figure 6: Fit of the Model: relationships between GHG emissions from food production, agricultural modernization and GDP per capita

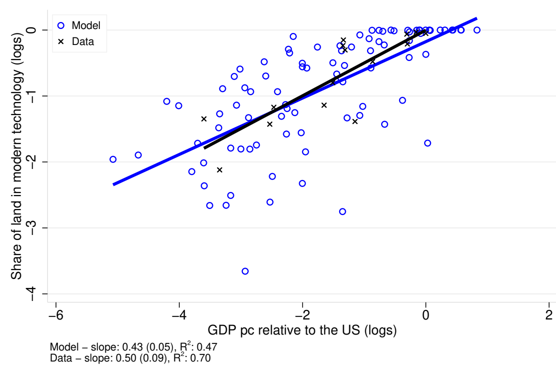
(a) Employment in Agriculture



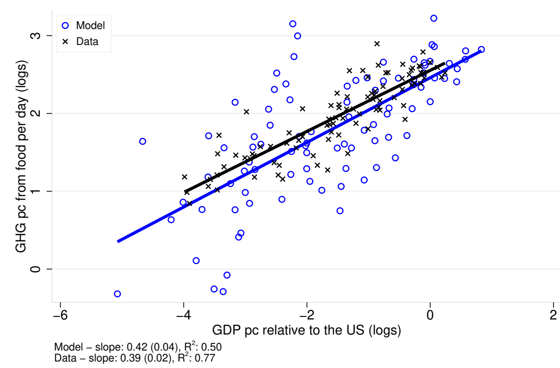
(b) Cost Share of Inputs



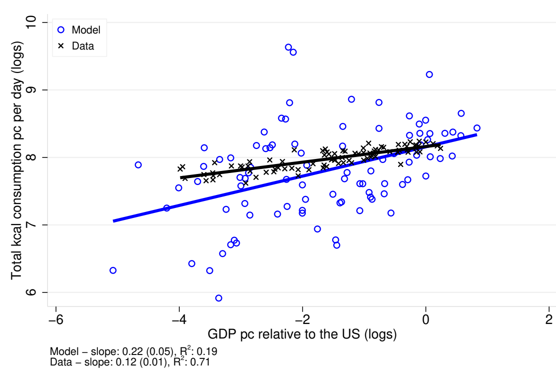
(c) Share of Land in Modern Technology



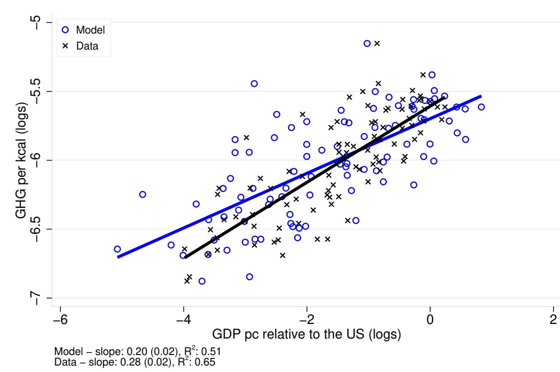
(d) Food GHG per capita



(e) Calories per capita



(f) Food GHG per calorie



Notes: This figure shows the fit of the model with the data in terms of the patterns of economic development. In the x-axis of each figure, we plot the level of GDP per capita predicted by the model. In black crosses, we have the actual data and, in blue circles, the model. The best linear fit predicted by the model is in blue and the best linear fit in the data in black.

5 Quantitative Exercises

In this section, we simulate our model to study the impact of economic development, dietary restrictions and food trade policies on GHG emissions from agriculture (section 5.2). Before doing so, we offer a decomposition of the role of different factors driving the relationships between GHG emissions and GDP per capita presented in Empirical Pattern 2 (section 5.1).

5.1 Decomposing the Relationship between Emissions and Income

Empirical Pattern 2 shows that GHG emissions from food is strongly increasing with GDP per capita in the data. Decomposing the drivers of this relationship is key for understanding the implications of economic development for GHG emissions. Part of the differences in emissions between rich and poor countries might stem from differences in the features of countries that would remain unaffected by economic growth in our framework. These confounding factors may include dietary preferences, comparative advantage in certain crops, or a country's geographic location.

In this section, we run counterfactuals to calculate the contribution of these factors through the lens of our model. Specifically, we remove the effect of a factor by equalizing across countries the parameters in the model that capture these factors, and simulate the new model-implied GHG emissions and GDP across countries. Table 3 presents our results. The regression coefficient on log GDP per capita is reported. In panel (a), the dependent variable is log GHG emissions from food consumption *per capita*, and panel (b) log GHG emissions from food consumption *per kcal*. Column (1) reports the coefficient estimate in our baseline calibration, which closely replicates Empirical Pattern 2 (Figure 2). The remaining columns present the coefficient estimate when the aforementioned features of the model are removed.

Column (2) removes the effect of intrinsic diet preferences, such as due to differences in demographics and culture. We set $a_{i,k}$ and $a_{i,A}$, which capture these preferences, equal across countries within each agricultural product, specifically equal to the population-weighted average, $\sum_{j \in \mathcal{I}} a_{j,k} \cdot \frac{N_j}{\sum_{j'} N_j}$ and $\sum_{j \in \mathcal{I}} a_{j,A} \cdot \frac{N_j}{\sum_{j'} N_j}$. The coefficient becomes about three-quarters smaller in size in Panel (a) and one-half smaller in Panel (b). That is, a large reason why food emissions is increasing with income in the cross-section is due to intrinsic preferences for diet: rich countries tend to consume emission-intense products not because they are richer, but because of dietary preferences that happen to be correlated with income. In Appendix Table O.2, we provide evidence of religion being one factor driving these preferences. In countries where Islam is dominant, the preference shifters, $a_{i,k}$, for pork relative to other types of meat are substantially lower; in countries where Hinduism is dominant, preferences for lamb, mutton and poultry, are stronger relative to other sources of meat.

Column (3) removes the effect of comparative advantage in agricultural production, by setting the productivity $T^f_{i,k\tau}$ to be the same across countries within each product and technology, specifically to the population-weighted average. Column (4) removes the effect of agricultural trade costs, by setting the domestic trade costs equal across countries within each agricultural, also based on the population-weighted average. In both cases, point-estimates remain similar or larger, suggesting that comparative advantage or geographic location are not driving these relationships.

Lastly, Column (5) removes all three features together. This means the resulting relationship between food emissions and income is only being driven by cross-country differences in the non-agricultural sectors. Intuitively, we can roughly understand this as exogenous variation in income being driven by differing productivities in the non-agricultural sectors. The coefficient is two-thirds smaller in Panel (a) and about a half in Panel (b), similar to the cases of column (2), which is expected given the other columns give little difference.

Summarizing, removing the confounding variation reveals a substantially attenuated relationship between food emissions and income. However, the effect of economic growth, such as originating in the non-agricultural sectors, still gives a meaningful contribution.

Table 3: Decomposing the Relationship between GHG Emissions from Food Consumption and Income

			Counterfactual		
	Baseline	Demand	Supply	Geography	All
	(1)	(2)	(3)	(4)	(5)
a. Dependent variable: Food GHG per capita					
Log of GDP pc	0.416***	0.080***	0.368***	0.398***	0.146***
	(0.043)	(0.031)	(0.043)	(0.067)	(0.025)
b. Dependent variable: Food GHG per calorie					
Log of GDP pc	0.198***	0.082***	0.238***	0.299***	0.118***
	(0.018)	(0.009)	(0.020)	(0.030)	(0.004)

Notes: * / ** / *** denotes significance at the 10 / 5 / 1 percent level. Each panel shows the coefficient from a different regression, with the dependent variable shown in the associated panel heading. Column (1) is under the baseline calibration of the model, column (2) under the counterfactual of equalized agricultural preferences, column (3) under equalized agricultural productivities, column (4) under equalized agricultural trade costs, and column (5) imposes the previous three simultaneously.

5.2 Effects of Economic Development, Dietary Restrictions and Food Trade Policies

We analyze the effect of various counterfactual policies, of academic and policy interest, on global GHG emissions from food and welfare, and offer a number of decompositions to quantify the important mechanisms of the model. Table 4 reports our results. Each row corresponds to a different counterfactual and each entry represents the percentage change relative to the baseline. Column (1) shows the effect on global welfare, which we measure as the average across countries, and column (2) the percentage point difference on the ratio of welfare between the top quartile (Q4) of countries in terms of GDP per capita and the bottom quartile (Q1). Column (3) shows the effects on global GHG emissions from food, including emissions from production and transportation, while column (4) shows the effect on emissions from transportation only.

To quantify the relevance of the nutrition transition, in column (5) we present the change in total emissions when this mechanism is shut down in the model. We implement this by re-calibrating the model and setting all income elasticity parameters, ϵ_k, in the agricultural sector equal, so that consumption of products within agriculture is homothetic, while still preserving non-homotheticity at the sectoral level.[24] In column (6), we shut down agricultural modernization by setting the within crop technology share by field, $\alpha^f_{i,k\tau}$, to be exogenously fixed.[25] In column (7), we shut down both simultaneously. To quantify the relevance of supply-side equilibrium adjustments in price, we calculate the change in emissions assuming supply is perfectly elastic in column (8). In column (9) we calculate the change in emissions using a benchmark, back-of-the-envelope method for each counterfactual.

Now, turning to the results.

Economic growth. The first row shows the impact of raising TFP of modern producers in agriculture, of non-agricultural producers, and of agricultural input producers, across the globe by 10 percent. This approach follows Gollin et al. (2007), who assume that traditional agriculture is not subject to innovation. In this counterfactual, global welfare increases by 14.9 percent, column (1), with the inequality between Q4 and Q1 increasing slightly by 0.4 percentage points, column (2). Global GHG emissions increase by 5.0 percent). The emissions from transportation increases by 2.2 percent. Since transportation represents only 5 percent of total emissions, its aggregate effect on GHG emissions is limited. Specifically, in levels, GHG emissions from production increases by 0.6 Gt CO2 and from transportation by 0.004 Gt CO2.

Column (5) shows that if we remove the nutrition transition, then the effect of emissions falls by 28 percent (1.4 percentage points). Column (6) shows that removing agricultural modernization reduces emissions by 16 percent (0.8 percentage points), and column (7) shows

[24]We set $\forall k$: $\epsilon_k = \epsilon_A$, where ϵ_A is chosen so that the income elasticity, equation (30), of every country is at most the value in the baseline calibration of 0.39-1. Under this calibration, the initial equilibrium is equivalent to that under the baseline calibration. The only difference is in the post-shock equilibrium.

[25]This is analogous to the fixed-crop counterfactual exercise in Costinot et al. (2016), who do not have technology choice.

Table 4: Aggregate Effects of Alternative Policies

	Welfare		Global GHG Emissions						
	Global	Q4/Q1	Total	Transp.	¬NT	¬AM	¬NT/AM	Demand	Mech.
Counterfactual	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TFP growth	14.9	0.4	5.0	2.2	3.6	4.2	2.9	10.0	15.3
No beef	-0.6	1.0	-20.0	-1.2	-19.9	-20.5	-20.4	-23.7	-28.9
Vegetarian	-2.8	6.0	-30.0	-4.0	-29.7	-30.8	-30.6	-37.3	-48.2
Eat local	-17.8	4.9	-11.9	-74.9	-9.3	-12.1	-9.3	-12.4	-4.6

Notes: This table shows the impact of different counterfactuals on global welfare and CO2 emissions. Each cell is a percentage change relative to the baseline. Column (1) is the change in aggregate welfare. Column (2) is the change in the ratio of the average welfare in the first quartile of the GDP per capita distribution versus the bottom quartile. Column (3) is the change in global GHG emissions. Column (4) is the change in global GHG emissions from food transportation — which represents 4.6 percent of total emissions in the baseline. Column (5) shows the change in global GHG emissions when we shut down the nutrition transition channel (NT), by simulating the model assuming no differences in income elasticities across food products, while fixing the income elasticity for the agricultural sector as a whole. Column (6) shows the change in global GHG emissions when we shut down the agricultural modernization channel (AM), by fixing the share of land used in modern versus traditional technologies in the counterfactual. Column (7) shuts down both NT and AM channel. Column (8) shows the impact when we assume that supply is perfectly elastic — i.e., when producer prices are fixed —, with the exception of the no beef and vegetarian counterfactuals, in which we increase the price of these food products to infinity. Column (9) is counterfactual specific: It shows a mechanical, back-of-the-envelope calculation of the impact of each counterfactual; see main text for details.

that removing both reduces emissions by 42 percent (2.1 percentage points). That is, both these mechanisms are quantitatively relevant.

Column (8) shows that if we ignore the equilibrium change in prices due to economic growth, then we would overstate the increase in emissions by 100 percent. Intuitively, the increase in demand for agricultural products induced by economic growth causes production prices to rise, due to upward-sloping agricultural supply. This attenuates the resulting increase in agricultural consumption and therefore emissions. Column (9) shows that if we were to assume a one-for-one increase in food demand with income, we would overstate the increase in emissions by three times. These exercises show that ignoring the reaction coming from the supply side of the economy, or ignoring the non-homotheticity of demand, severely overstates the effect of economic growth on global emissions.

Diet Restrictions. Rows two and three show counterfactuals in which the government bans production of specific types of food products: in row two, we consider a world where no-one can consume beef, and, in row three, a world where everyone is vegetarian. We implement this by setting TFPs in these sectors to virtually zero, essentially mimicking a sufficiently large tax (there will be no tax revenue because production goes to zero). Global welfare declines in both cases, by 0.6 and 2.8 percent, respectively. This welfare loss stems in part from love-for-variety in preferences across food products, and in part from changes in incomes—for example, important meat producers, such as Argentina and Uruguay, experience a welfare decrease of 3 and 4 percent, respectively, when meat is banned. This in part underlines the worse effect of the policies on the poorest nations, as shown in column (2). Total emissions, column (3), in both cases decline substantially, with the decline being especially greater in the vegetarian case. This is expected given meat products typically have greater emissions than non-meat products, and the vegetarian counterfactual reduces the consumption of more meat products than just no beef.

Removing the nutrition transition, agricultural modernization, or both, columns (5) to (7), marginally attenuates the reduction in emissions, suggesting that these mechanisms are not quantitatively relevant for these policies. This is intuitive given these mechanisms operate through changes in income, while these policies only have second order effects on income.

To gauge the importance of general equilibrium effects, in column (9) we measure the change in total GHG emissions that one would get from a back-of-the-envelope calculation, in which we simply remove from agriculture the emissions coming from these particular food products. The emission reductions are substantially attenuated when accounting for general equilibrium effects, column (3) vs column (9), by 32 and 38 percent, for no beef and vegetarian respectively. Column (8) offers an intermediate step which holds production prices fixed (except for beef and meat products which go to infinity due to the policy), but allows consumers to substitute to other products given now they do spend some of their income on beef or meat. The emissions reduction is slightly attenuated, as one would expect given they reduce beef or meat consumption, but increase consumption of other food products. These numbers show that back-of-the-envelope calculations would substantially overstate the benefits of adopting these dietary policies.

Food Trade Policy. Row four shows the counterfactual in which we raise agricultural trade costs to reduce emissions from food transportation by 75 percent. Eating locally substantially reduces global welfare, by 18 percent. The effect is particularly unequal across countries, with the loss greater in the poorest countries as shown in column (2). This is mostly because of the large share of income spent on food in poorer countries. The reductions in GHG emissions from food production amplify the reductions associated with transportation, since total agricultural production drops at the global level, leading to a total GHG emission reduction of 11.9 percent. Here, if we simply remove the emissions from transportation, which is equivalent to 4.6 percent of total emissions—the mechanical effect in column (9)—, we understate the overall impact of the policy.

6 Conclusion

Agriculture is a major source of global GHG emissions. Understanding the mechanisms underlying this is paramount for forecasting emissions as economies develop and for determining the appropriate policy response. In this paper, we study two key agricultural transformations — the nutrition transition and agricultural modernization — and build a quantitative, multi-country, general equilibrium model to measure their environmental implications.

We find that both mechanisms are important drivers of the increase in GHG emissions from agriculture as countries develop, contributing to about one third of the increase in emissions. We use the model to quantify the environmental, welfare and inequality effects of diet and food trade policies, which have a lot of interest to both academics and policymakers. We find that diet policies are superior to trade policies. In all cases, we find that accounting for equilibrium adjustments in food supply are key, with emissions significantly overstated if they are ignored. These findings highlight the value of using a quantitative model, such as the one we develop.

In pursuing this research, we build a comprehensive, global dataset on GHG emissions, food consumption, production, and trade. We document empirical patterns demonstrating relevance of diet and agricultural technology to climate change. And, methodologically, we prove a new identification result, permitting the estimation of income elasticities without price data, which is not typically available.

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Online Appendices for "Diet, Economic Development, and Climate Change"

Not for Publication

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OA Data Details

Trade, Consumption and Production. Bilateral trade data at the food product level is provided by FAO-STAT — these data is constructed based on COMTRADE data. We combine the information on bilateral flows with data on total revenues by food product, also available from FAO-STAT, to measure the apparent consumption of every country in each food product, that is $AC_{i,k} = R_{i,k} - X_{i,k} + M_{i,k}$. To do so, we construct a crosswalk between the food products in the bilateral trade data with the revenue data. By combining these two datasets, we can construct all the trade flows between countries for each food category, including the sales of a country to itself.

Dietary Energy Supply. Dietary energy supply (DES) in terms of calories per capita and day come from the Food Balance Sheets (FBS) from FAO, which are designed to provide a complete picture of the sources of calories intake for each country in the world. These are measures of apparent consumption of calories (i.e., production minus exports plus imports plus adjustments for stock), and they are constructed by combining information on trade, production and national surveys. Specifically, FAOSTAT converts the quantities of food available in every country to the dietary energy content of the edible portion of each food product, available for human consumption — from these data, we obtain measures of conversion between calories and raw physical quantities produced, which we use in our analysis to compute the emissions from transportation, which is based on a weight and kilometer base. This value is then divided by the population size and by 365 days to calculate the per capita daily dietary energy available. The FBS contains information on DES for 121 food categories. With that information, we can compute the share of calories that each country source from each food product. In some cases, the categories were broader than the final list of food products that we use, for example for vegetables. In these cases, we take the expenditure share on that food product (relative to that broad food category) to construct the share of calories coming from that food product, as such, our data construction respects the total calories coming from that food category in the data. From this dataset, we also obtain the total calories consumed by each country. We multiply the total calories consumed by each country by the share of calories coming from each food category to recover the total calories intake from each food product for each country.

GHG emissions. Data on GHG emissions by food product comes from Poore and Nemecek (2018), PN18. The original data constructed contain information from each study. We employ here the compilation provided by the authors containing the average GHG emissions by calorie across the world for each food product. Specifically, they provide information for 38 food products. We construct a crosswalk between their food products and our final set of products, which contains 47 food products. Appendix Figure O.1 shows the final distribution of GHG emissions by food product in our data.

We also bring in country-level data from EDGAR-FOOD on emissions from food production (Crippa et al., 2021). A key feature of these data is that the authors break down the GHG emissions into the different stages of agricultural production, such as production, packaging, land use change, and transport.

We combine the data from PN18 with EDGAR-FOOD to construct three measures of GHG emissions from food production. First, we construct a measure of emissions from food consumption. To do so, we multiply the calories each country consume of each food product by the average emission associated with that food product, according to data from PN18. To ensure internal consistency of the data. We adjust the global level of emissions from that measure to match the global level reported in EDGAR-FOOD. Second, we construct measures of GHG emissions from food production and transport, which come directly from EDGAR-FOOD. We include in food production all stages of production except transport. In these data, production accounts for 95% of the emissions from agriculture and transport for 5% .

Potential Yield. We gather potential yield data by food product and technology from FAO-GAEZ. The data is available for two types of technology, low- and high-input use. According to the definitions provided by FAO-GAEZ, the low-input technology corresponds to traditional methods of production associated with no use of inputs such as chemical fertilizers and pesticides, and the high-input use related to modern methods of production associated with the use of machinery. Importantly, potential yields are constructed based solely on the geological characteristics of a region, and not on the market conditions. See Farrokhi and Pellegrina (2023) and Costinot et al. (2016) for a more detailed discussion of these datasets.

The data from FAO-GAEZ is available for 30 crops. For 17 food products, data on potential yields is not available. In those cases, we combine the data on *potential* yields with *realized* yields data at the grid-level from Earthstat to generate the *potential* yield data for all the food products in our final dataset. Specifically, for each technology, we project the realized yield data from FAO-GAEZ using information on the potential yield for the 30 crops with information for that technology. If the grid has no potential yield in any of the 30 crops, we assume that the grid has zero potential yield in any crop.

OB Complementary Empirical Pattern

This section estimates the correlation between income elasticities and the intensity of CO2 emissions using household level data. In that case, we estimate the following equation:

$$X_{j,k}^{HH} = \alpha^{HH} \cdot \text{CO2pk}_{\ k} \cdot \text{Income}_j^{HH} + \gamma_j^{HH} + \varphi_k^{HH} + \iota_{r(j),k}^{HH} + \epsilon_{j,k}^{HH}, \tag{O.1}$$

where γ_j^{HH} and φ_k^{HH} are household and good fixed effects. In addition, we include a $\iota_{r(j),k}^{HH}$, which is a municipality-good fixed effect, which aims at capturing the influence of common prices. As before, here a positive α^{HH} would indicate a higher income elasticity of agricultural products with a higher CO2 emissions per kilo-calorie. Appendix Table O.1 shows that, in the household data, our point estimates are smaller. However, the qualitative results hold across specifications, with and without excluding meat products.

OC Details about the Model

OC.1 Expenditure shares with nested non-homothetic CES

We can solve this problem in steps. We start with the choice of $c_{ij,k}$,

$$\min_{c_{ji,k}} p_{ji,k}c_{ji,k} - \lambda_{i,k}\left[C_{i,k} - \left[\sum_{j\in\mathcal{I}} (a_{ji,k})^{\frac{1}{\eta}} (c_{ji,k})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}\right]$$

This minimization problem gives the equation for the share that country i buys of varieties from j ($\pi_{ji,k}$)

$$\beta_{ji,k} \equiv \frac{a_{ji,k}p_{ji,k}^{1-\eta}}{p_{i,k}^{1-\eta}},$$

where the price index is given by the Lagrangian $\lambda_{i,k}$

$$p_{i,k} \equiv \lambda_{i,k} = \left[\sum_{j\in\mathcal{I}} (p_{ji,k})^{1-\eta}\right]^{\frac{1}{1-\eta}}.$$

We now solve the choice of $C_{i,k}$ in the middle tier

$$\min_{C_{i,k}} p_{i,k}C_{i,k} + \tilde{\lambda}_{i,s}\left[\tilde{C}_{i,s} - \left[\sum_{k\in\mathcal{K}_s} \left(a_{i,k}U_i^{\epsilon_k-1}\right)^{\frac{1}{\kappa}} (C_{i,k})^{\frac{\kappa-1}{\kappa}}\right]^{\frac{\kappa}{\kappa-1}}\right].$$

The share of expenditure on good k from sector s is

$$\beta_{i,k} \equiv \frac{a_{i,k}U_i^{\epsilon_k-1}p_{i,k}^{1-\kappa}}{p_{i,s(k)}^{1-\kappa}},$$

where the price index is, again, given by the Lagrangian

$$\tilde{p}_{i,s(k)} \equiv \tilde{\lambda}_{i,s(k)} = \left[\sum_{k'\in\mathcal{K}_{s(k)}} a_{i,k'}U_i^{\epsilon_{k'}-1}p_{i,k'}^{1-\kappa}\right]^{\frac{1}{1-\kappa}}.$$

Lastly, in the upper tier, agents choose their consumption of $C_{i,s}$

$$\min_{\tilde{C}_{i,s}} \tilde{p}_{i,s}\tilde{C}_{i,k} + \bar{\lambda}_i\left[C_i - \left[\sum_{s\in\mathcal{S}} \left(a_{i,s}U_i^{\epsilon_s-1}\right)^{\frac{1}{\sigma}} \left(\tilde{C}_{i,s}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}\right].$$

The share of expenditure on sectoral composite good $\tilde{C}_{i,s}$ is

$$\bar{\beta}_{i,s} \equiv \frac{a_{i,s} U_i^{\epsilon_s - 1} \tilde{p}_{i,s}^{1-\sigma}}{P_i^{1-\sigma}},$$

where

$$P_i \equiv \bar{\lambda}_i = \left[\sum_{s \in \mathcal{S}} a_{i,s} U_i^{\epsilon_s - 1} \tilde{p}_{i,s}^{1-\sigma} \right]^{\frac{1}{1-\sigma}}.$$

Collecting the results above, we get the sales of country j to country i, $X_{ji,k}$, in the main body of the paper.

OC.2 Income Elasticities Derivation

OC.2.1 Product and Sector Income Elasticities, equations (28) and (30)

Elasticity of $\beta_{i,k}$:

$$\begin{aligned}
\frac{\partial \ln \beta_{i,k}}{\partial \ln E_i} &= \frac{\partial}{\partial \ln E_i} \ln \left[\frac{a_{i,k} U_i^{\epsilon_k} p_{i,k}^{1-\varsigma}}{\tilde{p}_{i,s(k)}^{1-\varsigma}} \right] \\
&= \epsilon_k \left(1 - \frac{\partial \ln P_i}{\partial \ln E_i} \right) - (1-\varsigma) \frac{\partial \ln \tilde{p}_{i,s(k)}}{\partial \ln E_i}, \quad \text{using eq (10)} \\
&= \epsilon_k \left(1 - \frac{\bar{\epsilon}_i}{1-\varsigma+\bar{\epsilon}_i} \right) - (1-\varsigma) \frac{\tilde{\epsilon}_{is}}{1-\varsigma+\bar{\epsilon}_i}, \quad \text{using eq (O.5), (O.7)} \\
&= (\epsilon_k - \tilde{\epsilon}_{is}) \frac{1-\varsigma}{1-\varsigma+\bar{\epsilon}_i} \qquad \text{(O.2)}
\end{aligned}$$

Elasticity of $\tilde{\beta}_{i,s}$:

$$\begin{aligned}
\frac{\partial \ln \tilde{\beta}_{i,s}}{\partial \ln E_i} &= \frac{\partial}{\partial \ln E_i} \ln \left[\frac{\tilde{a}_{i,s} \tilde{p}_{i,s}^{1-\sigma}}{P_i^{1-\sigma}}. \right] \\
&= (1-\sigma) \frac{\partial \ln \tilde{p}_{i,s}}{\partial \ln E_i} - (1-\sigma) \frac{\partial \ln P_i}{\partial \ln E_i} \\
&= (1-\sigma) \frac{\tilde{\epsilon}_{is}}{1-\varsigma+\bar{\epsilon}_i} - (1-\sigma) \frac{\bar{\epsilon}_i}{1-\varsigma+\bar{\epsilon}_i}, \quad \text{using eq (O.5), (O.7)} \\
&= \frac{1-\sigma}{1-\varsigma+\bar{\epsilon}_i} (\tilde{\epsilon}_{is} - \bar{\epsilon}_i) \qquad \text{(O.3)}
\end{aligned}$$

Elasticity of overall price index, P_i:

$$
\begin{aligned}
P_i^{1-\sigma} &= \sum_{s\in\mathcal{S}} \tilde{a}_{i,s}\tilde{p}_{i,s}^{1-\sigma}, \quad \text{using eq (9)} \\
(1-\sigma)\frac{\partial \ln P_i}{\partial \ln E_i} &= \sum_{s\in\mathcal{S}} \underbrace{\frac{\tilde{a}_{i,s}\tilde{p}_{i,s}^{1-\sigma}}{P_i^{1-\sigma}}}_{=\tilde{\beta}_{i,s}} \frac{\partial}{\partial \ln E_i} \ln\left[\tilde{a}_{i,s}\tilde{p}_{i,s}^{1-\sigma}\right], \quad \text{using eq (8)} \\
&= \sum_{s\in\mathcal{S}} \tilde{\beta}_{i,s}(1-\sigma)\frac{\partial \ln \tilde{p}_{i,s}}{\partial \ln E_i} \\
&= \sum_{s\in\mathcal{S}} \tilde{\beta}_{i,s}(1-\sigma)\left(1-\frac{\partial \ln P_i}{\partial \ln E_i}\right)\frac{\tilde{\epsilon}_{is}}{1-\varsigma}, \quad \text{using eq (O.6)} \qquad \text{(O.4)} \\
&= \left(1-\frac{\partial \ln P_i}{\partial \ln E_i}\right)\frac{1-\sigma}{1-\varsigma}\bar{\epsilon}_i, \quad \bar{\epsilon}_i \equiv \sum_{s\in\mathcal{S}} \tilde{\beta}_{i,s}\tilde{\epsilon}_{is} \\
\left(1-\sigma+\frac{1-\sigma}{1-\varsigma}\bar{\epsilon}_i\right)\frac{\partial \ln P_i}{\partial \ln E_i} &= \frac{1-\sigma}{1-\varsigma}\bar{\epsilon}_i \\
\frac{\partial \ln P_i}{\partial \ln E_i} &= \frac{\bar{\epsilon}_i}{1-\varsigma+\bar{\epsilon}_i} \qquad \text{(O.5)}
\end{aligned}
$$

Elasticity of sectoral price index, $\tilde{p}_{i,s}$:

$$
\begin{aligned}
\tilde{p}_{i,s}^{1-\varsigma} &\equiv \sum_{k\in\mathcal{K}_s} a_{i,k}U_i^{\epsilon_k}p_{i,k}^{1-\varsigma}, \quad \text{using eq (9)} \\
\frac{\partial \ln \tilde{p}_{i,s}^{1-\varsigma}}{\partial \ln E_i} &= \sum_{k\in\mathcal{K}_s} \underbrace{\frac{a_{i,k}p_{i,k}^{1-\varsigma}}{\tilde{p}_{i,s}^{1-\varsigma}}}_{=\beta_{i,k}} \frac{\partial \ln U_i^{\epsilon_k}}{\partial \ln E_i}, \quad \text{using eq (7)} \\
(1-\varsigma)\frac{\partial \ln \tilde{p}_{i,s}}{\partial \ln E_i} &= \left(1-\frac{\partial \ln P_i}{\partial \ln E_i}\right)\sum_{k\in\mathcal{K}_s} \beta_{i,k}\epsilon_k, \quad \text{using eq (10)} \\
&= \left(1-\frac{\partial \ln P_i}{\partial \ln E_i}\right)\tilde{\epsilon}_{i,s}, \quad \tilde{\epsilon}_{i,s} \equiv \sum_{k\in\mathcal{K}_s} \beta_{i,k}\epsilon_k \\
\frac{\partial \ln \tilde{p}_{i,s}}{\partial \ln E_i} &= \left(1-\frac{\partial \ln P_i}{\partial \ln E_i}\right)\frac{\tilde{\epsilon}_{i,s}}{1-\varsigma} \qquad \text{(O.6)} \\
&= \left(1-\frac{\bar{\epsilon}_i}{1-\varsigma+\bar{\epsilon}_i}\right)\frac{\tilde{\epsilon}_{i,s}}{1-\varsigma}, \quad \text{using eq (O.5)} \\
&= \frac{\tilde{\epsilon}_{i,s}}{1-\varsigma+\bar{\epsilon}_i} \qquad \text{(O.7)}
\end{aligned}
$$

OC.2.2 Relationship between Structural and Reduced Form, equation (33)

For k, k', k'' all in the same sector, s,

$$
\begin{aligned}
\frac{\delta_k - \delta_{k'}}{\delta_k - \delta_{k''}} &= \frac{\mathbb{E}_{i|k}\left[\frac{\partial \ln \beta_{i,k}}{\partial \ln E_i} + \frac{\partial \ln \tilde{\beta}_{i,s}}{\partial \ln E_i} + 1\right] - \mathbb{E}_{i|k'}\left[\frac{\partial \ln \beta_{i,k'}}{\partial \ln E_i} + \frac{\partial \ln \tilde{\beta}_{i,s}}{\partial \ln E_i} + 1\right]}{\mathbb{E}_{i|k}\left[\frac{\partial \ln \beta_{i,k}}{\partial \ln E_i} + \frac{\partial \ln \tilde{\beta}_{i,s}}{\partial \ln E_i} + 1\right] - \mathbb{E}_{i|k''}\left[\frac{\partial \ln \beta_{i,k''}}{\partial \ln E_i} + \frac{\partial \ln \tilde{\beta}_{i,s}}{\partial \ln E_i} + 1\right]} \\
&= \frac{\mathbb{E}_{i|k}\frac{\partial \ln \beta_{i,k}}{\partial \ln E_i} - \mathbb{E}_{i|k'}\frac{\partial \ln \beta_{i,k'}}{\partial \ln E_i}}{\mathbb{E}_{i|k}\frac{\partial \ln \beta_{i,k}}{\partial \ln E_i} - \mathbb{E}_{i|k''}\frac{\partial \ln \beta_{i,k''}}{\partial \ln E_i}} \\
&= \frac{\mathbb{E}_{i|k}\frac{1-\varsigma}{1-\varsigma+\bar{\epsilon}_i}\cdot\left(\epsilon_k - \tilde{\epsilon}_{i,s}\right) - \mathbb{E}_{i|k'}\frac{1-\varsigma}{1-\varsigma+\bar{\epsilon}_i}\cdot\left(\epsilon_{k'} - \tilde{\epsilon}_{i,s}\right)}{\mathbb{E}_{i|k}\frac{1-\varsigma}{1-\varsigma+\bar{\epsilon}_i}\cdot\left(\epsilon_k - \tilde{\epsilon}_{i,s}\right) - \mathbb{E}_{i|k''}\frac{1-\varsigma}{1-\varsigma+\bar{\epsilon}_i}\cdot\left(\epsilon_{k''} - \tilde{\epsilon}_{i,s}\right)} \\
&= \frac{\epsilon_k - \epsilon_{k'}}{\epsilon_k - \epsilon_{k''}}
\end{aligned}
$$

Where the first equality used equation (31) and that all products are in the same sector, $s(k) = s(k') = s(k'') = s$; the third equality used equation (28).

OC.3 Normalization of the Income Elasticity Parameters

In proposition 1, we show that one of the income elasticity parameters at the product level, $\{\epsilon_k\}_{k\in\mathcal{K}}$, (i.e. across all sectors, not per sector) is not identifiable and must be normalized. We prove that proposition here.

Proposition 1. (Product Income Elasticity Parameter Normalization) *Under equations (2), (3) and (4), utility maximization is invariant up to*

$$
k \in \mathcal{K}: \quad \epsilon_k \to \frac{\epsilon_k - \delta}{1 - \frac{\delta}{\varsigma}} \tag{O.8}
$$

for an arbitrary δ. Thus, for a single $k \in \mathcal{K}$, we can normalize $\epsilon_k \equiv 0$ without loss of generality.

Proof. Starting with the middle tier of utility, equation (3)

$$
\begin{aligned}
\tilde{C}_{i,s} &= \left[\sum_{k\in\mathcal{K}_s}\left(a_{i,k}U_i^{\epsilon_k}\right)^{\frac{1}{\varsigma}}\left(C_{i,k}\right)^{\frac{\varsigma-1}{\varsigma}}\right]^{\frac{\varsigma}{\varsigma-1}} \\
\tilde{C}^*_{i,s} \equiv U_i^{-\frac{\delta}{\varsigma}}\tilde{C}_{i,s} &= \left[\sum_{k\in\mathcal{K}_s}\left(a_{i,k}U_i^{\epsilon_k-\delta}\right)^{\frac{1}{\varsigma}}\left(C_{i,k}\right)^{\frac{\varsigma-1}{\varsigma}}\right]^{\frac{\varsigma}{\varsigma-1}}
\end{aligned} \tag{O.9}
$$

Rewriting the upper tier, equation (2), in terms of $\tilde{C}^*_{i,s}$

$$
\begin{aligned}
U_i &= \left[\sum_{s\in\mathcal{S}} (\tilde{a}_{i,s})^{\frac{1}{\sigma}}\, \tilde{C}_{i,s}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
&= \left[\sum_{s\in\mathcal{S}} (\tilde{a}_{i,s})^{\frac{1}{\sigma}} \left(U_i^{\frac{\delta}{\varsigma}} \tilde{C}^*_{i,s}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
U_i^* \equiv U_i^{1-\frac{\delta}{\varsigma}} &= \left[\sum_{s\in\mathcal{S}} (\tilde{a}_{i,s})^{\frac{1}{\sigma}} \left(\tilde{C}^*_{i,s}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}
\end{aligned}
\tag{O.10}
$$

Writing the middle tier, equation (O.9), in terms of U_i^*,

$$
\begin{aligned}
\tilde{C}^*_{i,s} &= \left[\sum_{k\in\mathcal{K}_s} \left(a_{i,k} U_i^{\epsilon_k-\delta}\right)^{\frac{1}{\varsigma}} (C_{i,k})^{\frac{\varsigma-1}{\varsigma}}\right]^{\frac{\varsigma}{\varsigma-1}} \\
&= \left[\sum_{k\in\mathcal{K}_s} \left(a_{i,k} \left(U_i^*\right)^{\frac{\epsilon_k-\delta}{1-\frac{\delta}{\varsigma}}}\right)^{\frac{1}{\varsigma}} (C_{i,k})^{\frac{\varsigma-1}{\varsigma}}\right]^{\frac{\varsigma}{\varsigma-1}}
\end{aligned}
\tag{O.11}
$$

With U_i^* relabelled to U_i, and $\tilde{C}^*_{i,s}$ relabelled to $\tilde{C}_{i,s}$, specifying the upper and middle tiers of utility using equations (O.10) and (O.11) instead of equations (2) and (3) gives identical behavior, as all operations applied are equivalences. Yet, the system has product income elasticity parameters $\frac{\epsilon_k-\delta}{1-\frac{\delta}{\varsigma}}$ in place of ϵ_k, Thus, the system is invariant to transform in equation (O.8).

In particular, for a single $k \in \mathcal{K}$, we can normalize $\epsilon_k \equiv 0$ by choosing δ so that $\frac{\epsilon_k-\delta}{1-\frac{\delta}{\varsigma}} = 0$. □

In proposition 2, we show that homothetic preference weights in the upper tier of utility, equation (2), is without loss of generality. To show this, consider a version of the upper tier with non-homothetic preference weights

$$
U_i = \left[\sum_{s\in\mathcal{S}} \left(\tilde{a}_{i,s} U_i^{\tilde{\epsilon}_s}\right)^{\frac{1}{\sigma}} \tilde{C}_{i,s}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}
\tag{O.12}
$$

with sectoral income elasticity parameters, $\tilde{\epsilon}_s$, that are analogous to the ϵ_k at the product level. In proposition 2, we show that all the sectoral income elasticity parameters can be normalized to zero, $\forall s \in \mathcal{S} : \tilde{\epsilon}_s \equiv 0$.

Proposition 2. (Sectoral Income Elasticity Parameter Normalization) *Under equations (O.12), (3) and (4), utility maximization is invariant up to*

$$
\forall k \in \mathcal{K}: \quad \epsilon_k \to \epsilon_k - \delta_{s(k)} \tag{O.13}
$$

$$
\forall s \in \mathcal{S}: \quad \tilde{\epsilon}_s \to \tilde{\epsilon}_s + \delta_s \frac{\sigma-1}{\varsigma} \tag{O.14}
$$

for arbitrary $\{\delta_s\}_{s\in\mathcal{S}}$. Thus, without loss of generality, we can normalize $\forall s \in \mathcal{S} : \tilde{\epsilon}_s \equiv 0$.

Proof. Starting with the middle tier of utility, equation (3)

$$\tilde{C}_{i,s} = \left[\sum_{k\in\mathcal{K}_s} \left(a_{i,k}U_i^{\epsilon_k}\right)^{\frac{1}{\varsigma}} \left(C_{i,k}\right)^{\frac{\varsigma-1}{\varsigma}}\right]^{\frac{\varsigma}{\varsigma-1}}$$

$$\tilde{C}^*_{i,s} \equiv \tilde{C}_{i,s}U_i^{-\frac{\delta_s}{\varsigma}} = \left[\sum_{k\in\mathcal{K}_s} \left(a_{i,k}U_i^{\epsilon_k-\delta_s}\right)^{\frac{1}{\varsigma}} \left(C_{i,k}\right)^{\frac{\varsigma-1}{\varsigma}}\right]^{\frac{\varsigma}{\varsigma-1}} \tag{O.15}$$

Rewriting the upper tier, equation (O.12), in terms of $\tilde{C}^*_{i,s}$

$$\begin{aligned} U_i &= \left[\sum_{s\in\mathcal{S}} \left(\tilde{a}_{i,s}U_i^{\tilde{\epsilon}_s}\right)^{\frac{1}{\sigma}} \tilde{C}_{i,s}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\ &= \left[\sum_{s\in\mathcal{S}} \left(\tilde{a}_{i,s}U_i^{\tilde{\epsilon}_s}\right)^{\frac{1}{\sigma}} \left(\tilde{C}^*_{i,s}U_i^{\frac{\delta_s}{\varsigma}}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\ &= \left[\sum_{s\in\mathcal{S}} \left(\tilde{a}_{i,s}U_i^{\tilde{\epsilon}_s+\delta_s\frac{\sigma-1}{\varsigma}}\right)^{\frac{1}{\sigma}} \left(\tilde{C}^*_{i,s}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \end{aligned} \tag{O.16}$$

With $\tilde{C}^*_{i,s}$ relabelled to $\tilde{C}_{i,s}$, specifying the upper and middle tiers of utility using equations (O.16) and (O.15) instead of equations (O.12) and (3) gives identical behavior, as all operations applied are equivalences. Yet, the system has sectoral income elasticity parameters $\tilde{\epsilon}_s + \delta_s\frac{\sigma-1}{\varsigma}$ in place of $\tilde{\epsilon}_s$, and product income elasticity parameters as $\epsilon_k - \delta_s$ in place of ϵ_k. Thus, the system is invariant to transform in equations (O.13) and (O.14).

In particular, we can normalize $\tilde{\epsilon}_s \equiv 0$ by choosing δ_s so that $\tilde{\epsilon}_s + \delta_s\frac{\sigma-1}{\varsigma} = 0$. □

OC.4 Analytic Counterfactual Derivation

Proving equation (34):

Proof. Totally differentiating equation (26),

$$\begin{aligned} \frac{\mathrm{d}\ln G_i^P}{\mathrm{d}\ln T_{i,NA}} &= \sum_{k\in\mathcal{K}_A}\sum_{\tau\in\{0,1\}} \frac{\varphi^P_{k\tau}Q_{i,k\tau}}{G_i}\cdot\frac{\mathrm{d}\ln Q_{i,k\tau}}{\mathrm{d}\ln T_{i,NA}} \\ &= \sum_{k\in\mathcal{K}_A}\sum_{\tau\in\{0,1\}} \frac{\varphi^P_{k\tau}Q_{i,k\tau}}{G_i}\cdot\frac{\partial\ln Q_{i,k\tau}}{\partial\ln\left(w_i,\boldsymbol{E}'\right)'}\cdot\frac{\mathrm{d}\ln\left(w_i,\boldsymbol{E}\right)}{\mathrm{d}\ln T_{i,NA}} \\ &+ \underbrace{\sum_{k\in\mathcal{K}_A}\sum_{\tau\in\{0,1\}} \frac{\varphi^P_{k\tau}Q_{i,k\tau}}{G_i}\cdot\frac{\partial\ln Q_{i,k\tau}}{\partial\ln\mathbf{p}'}\cdot\frac{\mathrm{d}\ln\mathbf{p}}{\mathrm{d}\ln T_{i,NA}}}_{\text{Price Effect}} \end{aligned} \tag{O.17}$$

in the second equality we used the chain rule. The second term is the price effect. Looking at the first term, we can rewrite this using

$$
\begin{aligned}
\frac{\partial \ln Q_{i,k\tau}}{\partial \ln (w_i, \boldsymbol{E}')'} &= \frac{\partial \ln \frac{Q_{i,k\tau}}{Q_{i,k}}}{\partial \ln (w_i, \boldsymbol{E}')'} + \frac{\partial \ln Q_{i,k}}{\partial \ln (w_i, \boldsymbol{E}')'} \\
&= \frac{\partial \ln \frac{Q_{i,k\tau}}{Q_{i,k}}}{\partial \ln w_i} + \frac{\partial \ln \left(\sum_{j \in \mathcal{I}} d_{ij,k} c_{ij,k} \right)}{\partial \ln \boldsymbol{E}'}
\end{aligned} \tag{O.18}
$$

where in the second inequality, we used market clearing $Q_{i,k} = \sum_{j \in \mathcal{I}} d_{ij,k} c_{ij,k}$ from equation (23), and that, conditional on prices, $\frac{Q_{i,k\tau}}{Q_{i,k}}$ is only a function of the wage, w_i, (from equation 15) and demand is only a function of income in each country, $\boldsymbol{E} \equiv \{E_i\}_{i \in \mathcal{I}}$ (from equations 6, 7, 8). Inserting equation (O.18) into equation (O.17) gives

$$
\begin{aligned}
\frac{\mathrm{d} \ln G_i^P}{\mathrm{d} \ln T_{i,NA}} = & \overbrace{\sum_{k \in \mathcal{K}_A} \sum_{\tau \in \{0,1\}} \frac{\varphi_{k\tau}^P Q_{i,k\tau}}{G_i^P} \cdot \frac{\partial \ln \frac{Q_{i,k\tau}}{Q_{i,k}}}{\partial \ln w_i} \cdot \frac{\mathrm{d} \ln w_i}{\mathrm{d} \ln T_{i,NA}}}^{\text{Agricultural Modernization}} \\
& + \sum_{k \in \mathcal{K}_A} \frac{\sum_{\tau \in \{0,1\}} \varphi_{k\tau}^P Q_{i,k\tau}}{G_i^P} \cdot \frac{\partial \ln \left(\sum_{j \in \mathcal{I}} d_{ij,k} c_{ij,k} \right)}{\partial \ln \boldsymbol{E}'} \cdot \frac{\mathrm{d} \ln \boldsymbol{E}}{\mathrm{d} \ln T_{i,NA}} \\
& \underbrace{+ \sum_{k \in \mathcal{K}_A} \sum_{\tau \in \{0,1\}} \frac{\varphi_{k\tau}^P Q_{i,k\tau}}{G_i^P} \cdot \frac{\partial \ln Q_{i,k\tau}}{\partial \ln \mathbf{p}'} \cdot \frac{\mathrm{d} \ln \mathbf{p}}{\mathrm{d} \ln T_{i,NA}}}_{\text{Price Effect}}
\end{aligned} \tag{O.19}
$$

The first term is agricultural modernization. Looking at the second term in equation (O.19), we can rewrite this using

$$
\begin{aligned}
\frac{\partial \ln \left(\sum_{j \in \mathcal{I}} d_{ij,k} c_{ij,k} \right)}{\partial \ln \boldsymbol{E}'} &= \sum_{j \in \mathcal{I}} \frac{d_{ij,k} c_{ij,k}}{Q_{i,k}} \frac{\partial \ln \left(\frac{a_{ij,k} p_{ij,k}^{1-\eta}}{p_{j,k}^{1-\eta}} \beta_{j,k} \tilde{p}_{j,A} \tilde{C}_{j,A} \right)}{\partial \ln \boldsymbol{E}'} \\
&= \sum_{j \in \mathcal{I}} \frac{X_{ij,k}}{Y_{i,k}} \frac{\partial \ln \beta_{j,k}}{\partial \ln E_j} + \sum_j \frac{X_{ij,k}}{Y_{i,k}} \frac{\partial \ln \left(\tilde{p}_{j,A} \tilde{C}_{j,A} \right)}{\partial \ln \boldsymbol{E}'}
\end{aligned} \tag{O.20}
$$

where in the first line we used equations (6) and (7), and in the second line we used that $\frac{d_{ij,k} c_{ij,k}}{Q_{i,k}} = \frac{p_i^F d_{ij,k} c_{ij,k}}{p_i^F Q_{i,k}} = \frac{X_{ij,k}}{Y_{i,k}}$, and that $\beta_{j,k} \tilde{p}_{j,A} \tilde{C}_{j,A}$, conditional on prices, only depends on E_j (by equations 6, 7).

Inserting equation (O.20) into equation (O.19) gives

$$
\begin{aligned}
\frac{\mathrm{d}\ln G_i^P}{\mathrm{d}\ln T_{i,NA}} =& \overbrace{\sum_{k\in\mathcal{K}_A}\sum_{\tau\in\{0,1\}}\frac{\varphi_{k\tau}^P Q_{i,k\tau}}{G_i^P}\cdot\frac{\partial\ln\frac{Q_{i,k\tau}}{Q_{i,k}}}{\partial\ln w_i}\cdot\frac{\mathrm{d}\ln w_i}{\mathrm{d}\ln T_{i,NA}}}^{\text{Agricultural Modernization}} + \overbrace{\sum_{j\in\mathcal{I}}\sum_{k\in\mathcal{K}_A}\frac{X_{ij,k}}{Y_{i,k}}\frac{\sum_{\tau\in\{0,1\}}\varphi_{k\tau}^P Q_{i,k\tau}}{G_i^P}\cdot\frac{\partial\ln\beta_{j,k}}{\partial\ln E_j}\cdot\frac{\mathrm{d}\ln E_j}{\mathrm{d}\ln T_{i,NA}}}^{\text{Nutrition Transition}} \\
&+\underbrace{\sum_{j\in\mathcal{I}}\sum_{k\in\mathcal{K}_A}\frac{X_{ij,k}}{Y_{i,k}}\frac{\sum_{\tau\in\{0,1\}}\varphi_{k\tau}^P Q_{i,k\tau}}{G_i^P}\cdot\frac{\partial\ln\left(\tilde{p}_{j,A}\tilde{C}_{j,A}\right)}{\partial\ln \boldsymbol{E}'}\cdot\frac{\mathrm{d}\ln E_j}{\mathrm{d}\ln T_{i,NA}}}_{\text{Scale Effect}} \\
&+\underbrace{\sum_{k\in\mathcal{K}_A}\sum_{\tau\in\{0,1\}}\frac{\varphi_{k\tau}^P Q_{i,k\tau}}{G_i^P}\cdot\frac{\partial\ln Q_{i,k\tau}}{\partial\ln\mathbf{p}'}\cdot\frac{\mathrm{d}\ln\mathbf{p}}{\mathrm{d}\ln T_{i,NA}}}_{\text{Price Effect}} \qquad\qquad (\text{O.21})
\end{aligned}
$$

which is the decomposition given in equation (34).

Proving equation (35):

Taking the derivative,

$$
\begin{aligned}
\frac{\partial\ln\frac{Q_{i,k\tau}}{Q_{i,k}}}{\partial\ln w_i} &= \sum_{\tau'\in\{0,1\}}\left(I_{\tau,\tau'}-\frac{Q_{i,k\tau'}}{Q_{i,k}}\right)\frac{\partial\ln Q_{i,k\tau'}}{\partial\ln w_i} \\
&= \sum_{\tau'\in\{0,1\}}\left(I_{\tau,\tau'}-\frac{Q_{i,k\tau'}}{Q_{i,k}}\right)\sum_f\frac{Q_{i,k\tau'}^f}{Q_{i,k\tau'}}\left\{\frac{\partial\ln h_{i,k\tau'}^f}{\partial\ln w_i}+\frac{\theta_2-1}{\theta_2}\frac{\partial\ln\alpha_{i,k\tau'}^f}{\partial\ln w_i}+\frac{\theta_1-1}{\theta_1}\frac{\partial\ln\alpha_{i,k}^f}{\partial\ln w_i}\right\} \\
&\overset{|\mathcal{F}_i|=1}{=} \sum_{\tau'\in\{0,1\}}\left(I_{\tau,\tau'}-\frac{Q_{i,k\tau'}}{Q_{i,k}}\right)\left\{\frac{\partial\ln h_{i,k\tau'}^f}{\partial\ln w_i}+\frac{\theta_2-1}{\theta_2}\frac{\partial\ln\alpha_{i,k\tau'}^f}{\partial\ln w_i}\right\} \qquad (\text{O.22})
\end{aligned}
$$

where the first line used $Q_{i,k}=\sum_{\tau'\in\{0,1\}}Q_{i,k\tau'}$ and the second line used equation (15). The third line used the assumption of one field in country i, $|\mathcal{F}_i|=1$, which implies $\frac{Q_{i,k\tau'}^f}{Q_{i,k\tau'}}=1$, and note that the third term goes to zero because $\frac{\theta_1-1}{\theta_1}\frac{\partial\ln\alpha_{i,k}^f}{\partial\ln w_i}$ doesn't depend on τ. The first term in equation (O.22) can be rewritten using

$$
\begin{aligned}
\sum_{\tau'}\left(I_{\tau,\tau'}-\frac{Q_{i,k\tau'}}{Q_{i,k}}\right)\frac{\partial\ln h_{i,k\tau'}^f}{\partial\ln w_i} &= \overbrace{\left(1-\frac{Q_{i,k\tau}}{Q_{i,k}}\right)}^{=\frac{Q_{i,k,1-\tau}}{Q_{i,k}}}\frac{\partial\ln h_{i,k\tau}^f}{\partial\ln w_i}-\frac{Q_{i,k,1-\tau}}{Q_{i,k}}\frac{\partial\ln h_{i,k,1-\tau}^f}{\partial\ln w_i} \\
&= \frac{Q_{i,k,1-\tau}}{Q_{i,k}}\left(\frac{\partial\ln h_{i,k\tau}^f}{\partial\ln w_i}-\frac{\partial\ln h_{i,k,1-\tau}^f}{\partial\ln w_i}\right) \\
&= -\frac{Q_{i,k,1-\tau}}{Q_{i,k}}\left(\frac{\gamma_{k\tau}^N}{\gamma_{k\tau}^L}-\frac{\gamma_{k,1-\tau}^N}{\gamma_{k,1-\tau}^L}\right) \qquad (\text{O.23})
\end{aligned}
$$

where the third equality used that $\frac{\partial\ln h_{i,k\tau}^f}{\partial\ln w_i}=-\frac{\gamma_{k\tau}^N}{\gamma_{k\tau}^L}$, by equation (11). The second term in equation

(O.22) can be rewritten using

$$\sum_{\tau'\in\{0,1\}}\left(I_{\tau,\tau'}-\frac{Q_{i,k\tau'}}{Q_{i,k}}\right)\frac{\partial\ln\alpha^f_{i,k\tau'}}{\partial\ln w_i}=\overbrace{\left(1-\frac{Q_{i,k\tau}}{Q_{i,k}}\right)}^{=\frac{Q_{i,k,1-\tau}}{Q_{i,k}}}\frac{\partial\ln\alpha^f_{i,k\tau}}{\partial\ln w_i}-\frac{Q_{i,k,1-\tau}}{Q_{i,k}}\frac{\partial\ln\alpha^f_{i,k,1-\tau}}{\partial\ln w_i}$$
$$=\frac{Q_{i,k,1-\tau}}{Q_{i,k}}\left(\frac{\partial\ln\alpha^f_{i,k\tau}}{\partial\ln w_i}-\frac{\partial\ln\alpha^f_{i,k,1-\tau}}{\partial\ln w_i}\right)$$
$$=\frac{Q_{i,k,1-\tau}}{Q_{i,k}}\frac{1}{1-\alpha^f_{i,k\tau}}\frac{\partial\ln\alpha^f_{i,k\tau}}{\partial\ln w_i}$$
$$=-\theta_2\frac{Q_{i,k,1-\tau}}{Q_{i,k}}\left(\frac{\gamma^N_{k\tau}}{\gamma^L_{k\tau}}-\frac{\gamma^N_{k,1-\tau}}{\gamma^L_{k,1-\tau}}\right)$$

where the third equality used $\mathrm{d}\ln\alpha^f_{i,k,1-\tau}=-\frac{\alpha^f_{i,k\tau}}{1-\alpha^f_{i,k\tau}}\mathrm{d}\ln\alpha^f_{i,k\tau}$. The last equality used

$$\frac{\partial\ln\alpha^f_{i,k\tau}}{\partial\ln w_i}=\theta_2\left(\frac{\partial\ln h^f_{i,k\tau}}{\partial\ln w_i}-\frac{\partial\ln H^f_{i,k}}{\partial\ln w_i}\right)$$
$$=\theta_2\left(\frac{\partial\ln h^f_{i,k\tau}}{\partial\ln w_i}-\sum_{\tau'\in\{0,1\}}\alpha^f_{i,k\tau'}\frac{\partial\ln h_{i,k\tau'}}{\partial\ln w_i}\right)$$
$$=\theta_2\alpha^f_{i,k,1-\tau}\left(\frac{\partial\ln h^f_{i,k\tau}}{\partial\ln w_i}-\frac{\partial\ln h_{i,k,1-\tau}}{\partial\ln w_i}\right)$$
$$=-\theta_2\alpha^f_{i,k,1-\tau}\left(\frac{\gamma^N_{k\tau}}{\gamma^L_{k\tau}}-\frac{\gamma^N_{k,1-\tau}}{\gamma^L_{k,1-\tau}}\right)\tag{O.24}$$

where the first equality used equation (13), the second equality used equation (14), and the last equality used $\frac{\partial\ln h^f_{i,k\tau}}{\partial\ln w_i}=-\frac{\gamma^N_{k\tau}}{\gamma^L_{k\tau}}$. Inserting equations (O.23) and (O.24) into equation (O.22) gives

$$\frac{\partial\ln\frac{Q_{i,k\tau}}{Q_{i,k}}}{\partial\ln w_i}=-\frac{Q_{i,k,1-\tau}}{Q_{i,k}}\left(\frac{\gamma^N_{k\tau}}{\gamma^L_{k\tau}}-\frac{\gamma^N_{k,1-\tau}}{\gamma^L_{k,1-\tau}}\right)-\frac{\theta_2-1}{\theta_2}\theta_2\frac{Q_{i,k,1-\tau}}{Q_{i,k}}\frac{1}{1-\alpha^f_{i,k\tau}}\left(\frac{\gamma^N_{k\tau}}{\gamma^L_{k\tau}}-\frac{\gamma^N_{k,1-\tau}}{\gamma^L_{k,1-\tau}}\right)$$
$$=\theta_2\frac{Q_{i,k,1-\tau}}{Q_{i,k}}\left(\frac{\gamma^N_{k,1-\tau}}{\gamma^L_{k,1-\tau}}-\frac{\gamma^N_{k\tau}}{\gamma^L_{k\tau}}\right)$$

which is the desired expression, equation (35) □

OD Quantifying the Model

This section provides details about the quantification of the model. We first show a complete derivation of the estimating equations for the income elasticity—Section 4.1 in the main body of the paper. We then provide a full description of our calibration procedure—Section 4.1.2 in the main body of the paper

OD.1 Step 1: Estimation of Income Elasticities

Here, we provide a complete derivation of the equations that we use to estimate income elasticities in the paper.

Derivation of equation (38): starting from equation (6)

$$
\begin{aligned}
\beta_{ji,k} &= \frac{a_{ji,k} p_{ji,k}^{1-\eta}}{p_{i,k}^{1-\eta}} \\
\implies p_{i,k}^{1-\eta} &= \frac{a_{ji,k} p_{ji,k}^{1-\eta}}{\beta_{ji,k}} \\
(1-\eta)\ln p_{i,k} &= -\ln \beta_{ji,k} + (1-\eta)\ln\left(p_{j,k}^{F} d_{ji,k}\right) + \ln a_{ji,k}, \quad \text{using eq (20)} \\
&= -\ln \beta_{ji,k} + (1-\eta)\ln p_{j,k}^{F} + \ln\left(a_{ji,k} d_{ji,k}^{1-\eta}\right) \\
(1-\eta)\ln p_{i,k} &= -\frac{1}{N_{\mathcal{I}_{i,k}^{\neg 0}}} \sum_{j\in\mathcal{I}_{i,k}^{\neg 0}} \ln \beta_{ji,k} + (1-\eta)\frac{1}{N_{\mathcal{I}_{i,k}^{\neg 0}}} \sum_{j\in\mathcal{I}_{i,k}^{\neg 0}} \ln p_{j,k}^{F} + \frac{1}{N_{\mathcal{I}_{i,k}^{\neg 0}}} \sum_{j\in\mathcal{I}_{i,k}^{\neg 0}} \ln\left(a_{ji,k} d_{ji,k}^{1-\eta}\right)
\end{aligned}
$$

Derivation of equation (39): starting from equation (7) for $k \neq k^*$

$$
\begin{aligned}
\beta_{i,k} &= \frac{a_{i,k} U_i^{\epsilon_k} p_{i,k}^{1-\varsigma}}{\tilde{p}_{i,s(k)}^{1-\varsigma}} \\
&= \frac{a_{i,k} \left(E_i/P_i\right)^{\epsilon_k} p_{i,k}^{1-\varsigma}}{\tilde{p}_{i,s(k)}^{1-\varsigma}}, \quad \text{using eq (10)} \\
\ln \beta_{i,k} &= \epsilon_k \ln E_i - \epsilon_k \ln P_i + (1-\varsigma)\ln p_{i,k} - (1-\varsigma)\ln \tilde{p}_{i,s(k)} + \ln a_{i,k} \\
&= \epsilon_k \ln E_i - \epsilon_k \ln P_i + (1-\varsigma)\ln p_{i,k} - \left(\frac{1-\varsigma}{1-\sigma}\right)\ln\left(\frac{\tilde{\beta}_{i,s(k)} P_i^{1-\sigma}}{\tilde{a}_{i,s(k)}}\right) + \ln a_{i,k}, \quad \text{using eq (37)} \\
&= \epsilon_k \ln E_i - \left(\frac{1-\varsigma}{1-\sigma}\right)\ln \tilde{\beta}_{i,s(k)} + \frac{\epsilon_k + (1-\varsigma)}{1-\sigma}\ln \tilde{\beta}_{i,s(k^*)} - \left[\epsilon_k + (1-\varsigma)\right]\left[-\frac{1}{1-\eta}\ln \hat{\beta}_{i,k^*} + \ln \hat{p}_{\mathcal{I}_{i,k^*}^{\neg 0},k^*}^{F}\right] + \cdots
\end{aligned}
$$

$$
\begin{aligned}
&= \epsilon_k \ln E_i - \left(\frac{1-\varsigma}{1-\sigma}\right)\ln \tilde{\beta}_{i,s(k)} - \left[\epsilon_k + (1-\varsigma)\right]\ln P_i + (1-\varsigma)\ln p_{i,k} + \ln\left(a_{i,k}\tilde{a}_{i,s(k)}^{\frac{1-\varsigma}{1-\sigma}}\right) \\
&= \epsilon_k \ln E_i - \left(\frac{1-\varsigma}{1-\sigma}\right)\ln \tilde{\beta}_{i,s(k)} - \frac{\epsilon_k + (1-\varsigma)}{1-\sigma}\ln\left(\frac{\tilde{a}_{i,s(k^*)} a_{i,k^*}^{\frac{1-\sigma}{1-\varsigma}} p_{i,k^*}^{1-\sigma}}{\tilde{\beta}_{i,s(k^*)}}\right) + (1-\varsigma)\ln p_{i,k} + \cdots \\
&\cdots + \ln\left(a_{i,k}\tilde{a}_{i,s(k)}^{\frac{1-\varsigma}{1-\sigma}}\right), \quad \text{using eq (36)} \\
&= \epsilon_k \ln E_i - \left(\frac{1-\varsigma}{1-\sigma}\right)\ln \tilde{\beta}_{i,s(k)} + \frac{\epsilon_k + (1-\varsigma)}{1-\sigma}\ln \tilde{\beta}_{i,s(k^*)} - \left[\epsilon_k + (1-\varsigma)\right]\ln p_{i,k^*} + (1-\varsigma)\ln p_{i,k} + \cdots \\
&\cdots + \underbrace{\ln\left(\frac{a_{i,k}\tilde{a}_{i,s(k)}^{\frac{1-\varsigma}{1-\sigma}}}{\tilde{a}_{i,s(k^*)}^{\frac{\epsilon_k+(1-\varsigma)}{1-\sigma}} a_{i,k^*}^{\frac{\epsilon_k+(1-\varsigma)}{1-\varsigma}}}\right)}_{\equiv f_{i,k}(a)} \\
&= \epsilon_k \ln E_i - \left(\frac{1-\varsigma}{1-\sigma}\right)\ln \tilde{\beta}_{i,s(k)} + \frac{\epsilon_k + (1-\varsigma)}{1-\sigma}\ln \tilde{\beta}_{i,s(k^*)} - \left[\epsilon_k + (1-\varsigma)\right]\left[-\frac{1}{1-\eta}\ln \hat{\beta}_{i,k^*} + \ln \hat{p}_{\mathcal{I}_{i,k^*}^{\neg 0},k^*}^{F}\right] + \cdots
\end{aligned}
$$

$$
\cdots + (1-\varsigma)\left[-\frac{1}{1-\eta}\ln\hat{\beta}_{i,k} + \ln\hat{p}^{F}_{\mathcal{I}^{\neg 0}_{i,k},k}\right] + f_{i,k}(a), \quad \text{using eq (38)}
$$

$$
= \epsilon_k \ln E_i - \left(\frac{1-\varsigma}{1-\sigma}\right)\ln\tilde{\beta}_{i,s(k)} + \frac{\epsilon_k + 1 - \varsigma}{1-\sigma}\ln\tilde{\beta}_{i,s(k^*)} + \frac{\epsilon_k + 1 - \varsigma}{1-\eta}\ln\hat{\beta}_{i,k^*} - \frac{1-\varsigma}{1-\eta}\ln\hat{\beta}_{i,k} + \cdots
$$

$$
\cdots + \underbrace{-\left[\epsilon_k + (1-\varsigma)\right]}_{=[\varsigma - 1 - \epsilon_k]}\ln\hat{p}^{F}_{\mathcal{I}^{\neg 0}_{i,k^*},k^*} + (1-\varsigma)\ln\hat{p}^{F}_{\mathcal{I}^{\neg 0}_{i,k},k} + f_{i,k}(a)
$$

OD.2 Step 2: Technology Parameters, Productivity Shifters and Preference Shifters

This section describes the calibration of the model, once with income elasticities estimated in step 1.

Production Technologies.

We pick technological parameters from the literature, specifically, θ_1, θ_2. For the factors and intermediate input shares, $\gamma^L_{k\tau}$, $\gamma^N_{k\tau}$, $\gamma^M_{k\tau}$ and $\lambda_{kk'}$. We proceed as follows. First, we obtain cost share data, $\bar{\gamma}^L_k$, $\bar{\gamma}^N_k$, and $\bar{\gamma}^M_k$, for the United States, which is a weighted average by total sales of the cost share of each input across modern and traditional technologies. The land share in modern technologies is approximately 95 percent in the US, we use that share as a *proxy* for the share of sales, and denote that share as ω_1 and ω_0 for modern and traditional technologies respectively. Lastly, we pick the ratio of $\tilde{\gamma} = \gamma^L_{k1}/\gamma^L_{k0} = 2.67$, which is calibrated in Farrokhi and Pellegrina (2023). With these statistics, we can calibrate factor shares using the following equations

$$
\begin{aligned}
\gamma^L_{k0} &= \left(\bar{\gamma}^L_k - \gamma^L_{k0}\omega_0\right)/\omega_1 \\
\gamma^L_{k1} &= \tilde{\gamma}\gamma^L_{k0} \\
\gamma^N_{k0} &= 1 - \gamma^L_{k0} \\
\gamma^N_{k1} &= 1 - \gamma^L_{k1} - \gamma^M_{k1} \\
\gamma^M_{k0} &= 0 \\
\gamma^M_{k1} &= \bar{\gamma}^M_k/\omega_1
\end{aligned}
$$

We get $\{\gamma^L_{k0}, \gamma^N_{k0}, \gamma^M_{k0}\gamma^L_{k1}, \gamma^N_{k1}, \gamma^M_{k1}\} = \{0.503, 0.497, 0, 0.189, 0.189, 0.622\}$ and $\{\lambda_{kF}, \lambda_{kP}, \lambda_{kC}\} = \{0.256, 0.158, 0.586\}$.

Trade Costs.

We start by running, for every good in the economy, a gravity equation

$$
\log X_{ji,k} = \underbrace{\mathrm{FE}_{j,k}}_{(1-\eta)\log\left(p^F_{j,k}\right)} + \underbrace{\mathrm{FE}_{i,k}}_{\log\left(\tilde{\beta}_{j,k}\beta_{j,s(k)}E_j\right)} + \underbrace{\epsilon_{ij,k}}_{\log\left(a_{ji,k}d^{1-\eta}_{ji,k}\right)},
$$

we recover the predicted values from the origin fixed effect $\mathrm{FE}_{j,k}$, which we call $\mathrm{FE}^{data}_{j,k}$, and the residuals $\epsilon_{ij,k}$. We construct the trade cost matrix directly from the residuals from the regression, by taking its exponential.

Land Productivity.

For the grid-level TFPs, we proceed as follows. First, we define total yields in FAO-GAEZ as

$$y_{i,k\tau}^{f,GAEZ} = \bar{h}_{k\tau}^{GAEZ} T_{i,k\tau}^{f}$$

where $\bar{h}_{k\tau}^{GAEZ}$ captures the implicit market and technological assumptions used by FAO-GAEZ in the construction of the data. Importantly, notice that this variable is independent of the country i and grid f. Therefore, the ratio of grid-level TFPs can be recovered directly from the data

$$\frac{y_{i,k\tau}^{f,GAEZ}}{y_{i,k\tau}^{f',GAEZ}} = \frac{T_{i,k\tau}^{f}}{T_{i,k\tau}^{f'}}.$$

The global level of TFP from FAO-GAEZ, since it depends on unobserved market assumptions $\bar{h}_{k\tau}^{GAEZ}$, is not separately identified $T_{i,k\tau}^{f}$ only from the FAO-GAEZ data—even though the relative values are. Having that in mind, we write our measure of grid-level TFP as

$$\widehat{T}_{i,k\tau}^{f} = T_{k\tau} y_{i,k\tau}^{f,GAEZ},$$

and calibrate the global level of TFP, $T_{k\tau}$, within our algorithm.

Calibration Algorithm.

Turning now to the calibration.

1. Guess $(T_{k0})^g$, $(T_{k1})^g$ $(\tilde{a}_{i,s})^g$, $(a_{i,k})^g$, $(T_{i,k})^g$
2. Construct model-implied $\text{FE}_{j,k}^{model}$ for every $k \in \{NA, F, P, M\}$
   (a) Compute $\text{diff}\,(\text{FE}_{j,k}) = |\text{FE}_{j,k}^{model} - \text{FE}_{j,k}^{data}|$
   (b) Update $(T_{k\tau})^{g+1}$ based on $\text{diff}\,(\text{FE}_{j,k})$
3. Construct model-implied $\beta_{j,s}^{model}$
   (a) Compute $\text{diff}\,(\beta_{j,s}) = |\beta_{j,s}^{model} - \beta_{j,s}^{data}|$
   (b) Update $(\tilde{a}_{i,s})^{g+1}$ based on $\text{diff}\,(\beta_{j,s})$
4. Construct model-implied $\beta_{j,k}^{C,model}$, the share of calories that country j source from food product k
   (a) Compute $\text{diff}\,(\beta_{j,k}) = |\beta_{j,k}^{C,model} - \beta_{j,k}^{C,data}|$
   (b) Update $(a_{i,k})^{g+1}$ based on $\text{diff}\,(\beta_{j,k})$

5. Construct model-implied $\bar{\alpha}_{USA,k}$, the share of land in the US employed in modern agriculture

   (a) Compute $\text{diff}\left(\bar{\alpha}_{USA,k}\right) = |\bar{\alpha}_{USA,k}^{model} - \bar{\alpha}_{USA,k}^{data}|$

   (b) Update $(T_{k1})^{g+1}$ based on $\text{diff}\left(\bar{\alpha}_{USA,k}\right)$

6. Construct model-implied $Q_k^{model} = \sum_i \sum_\tau Q_{i,k\tau}$, total quantities produced of good k

   (a) Compute $\text{diff}\left(Q_k\right) = |Q_k^{model} - Q_k^{data}|$

   (b) Update $(T_{k0})^{g+1}$ based on $\text{diff}\left(Q_k\right)$

7. Check diff $=\max\{\text{diff}(\text{FE}_{j,k}), \text{diff}\left(\beta_{j,s}\right), \text{diff}\left(\bar{\alpha}_{USA,k}\right), \text{diff}\left(Q_k\right)\}$

   (a) if diff $> \epsilon$ then take $(T_{k0})^{g+1}, (T_{k1})^{g+1} \left(\tilde{a}_{i,s}\right)^{g+1}, \left(a_{i,k}\right)^{g+1}, \left(T_{i,k}\right)^{g+1}$ and return to step 2

   (b) if diff $< \epsilon$ then finish the algorithm

OE Online Appendix Tables and Figures

Table O.1: Income Elasticity and GHG Emissions per calorie

	Specification		
	(1)	(2)	(3)
a. All products			
$\log(\text{HHINCOME})_i \times \log(\text{GHGPK})_k$	0.043***	0.025***	0.016***
	(0.001)	(0.002)	(0.003)
R2	0.483	0.654	0.800
Obs	264928	264928	264928
b. Excluding meat products			
$\log(\text{HHINCOME})_i \times \log(\text{GHGPK})_k$	0.020***	0.030***	0.010***
	(0.001)	(0.002)	(0.003)
R2	0.462	0.594	0.777
Obs	212768	212768	212768
Controls			
- Household FE	Y	Y	Y
- Good FE	-	Y	Y
- Municipality-Good FE	-	-	Y

Notes: * / ** / *** denotes significance at the 10 / 5 / 1 percent level. Robust standard errors clustered at the household level reported in parenthesis. Panel (b) exludes beef, lamb and mutton, pig meat and poultry meat.

Table O.2: Preferences for different types of Meat by Religion

	(1)	(2)
	Pig meat	Lamb, Mutton, and Poultry
Dominant Muslim	-1.467***	
	(0.481)	
Dominant Hindu		0.415*
		(0.213)
Observations	91	91
Adjusted R^2	0.080	0.029

Notes: * / ** / *** denotes significance at the 10 / 5 / 1 percent level. Robust standard errors clustered. This table shows the relationship between model-implied preference shifters for different types of meat products and observables related to religion. “Dominant Muslim” equals to 1 if a country has more than 75 percent of its population who is considered Muslim and zero otherwise. “Dominant Hindu” is the analogous variable for Hindu. The dependent variable in column (1) is the preference shifter for pork relative to four meat categories: (1) bovine meat, (2) lamb and mutton, (3) chicken, and (4) pork.

Table O.3: Welfare Impact across Quartiles of GDP per capita

Counterfactual	q1 (1)	q2 (2)	q3 (3)	q4 (4)
TFP growth	14.5	14.6	14.7	15.0
No beef	-1.4	-1.3	-0.9	-0.4
Vegetarian	-7.7	-4.3	-3.6	-2.2
Eat local	-20.5	-45.9	-13.3	-16.6

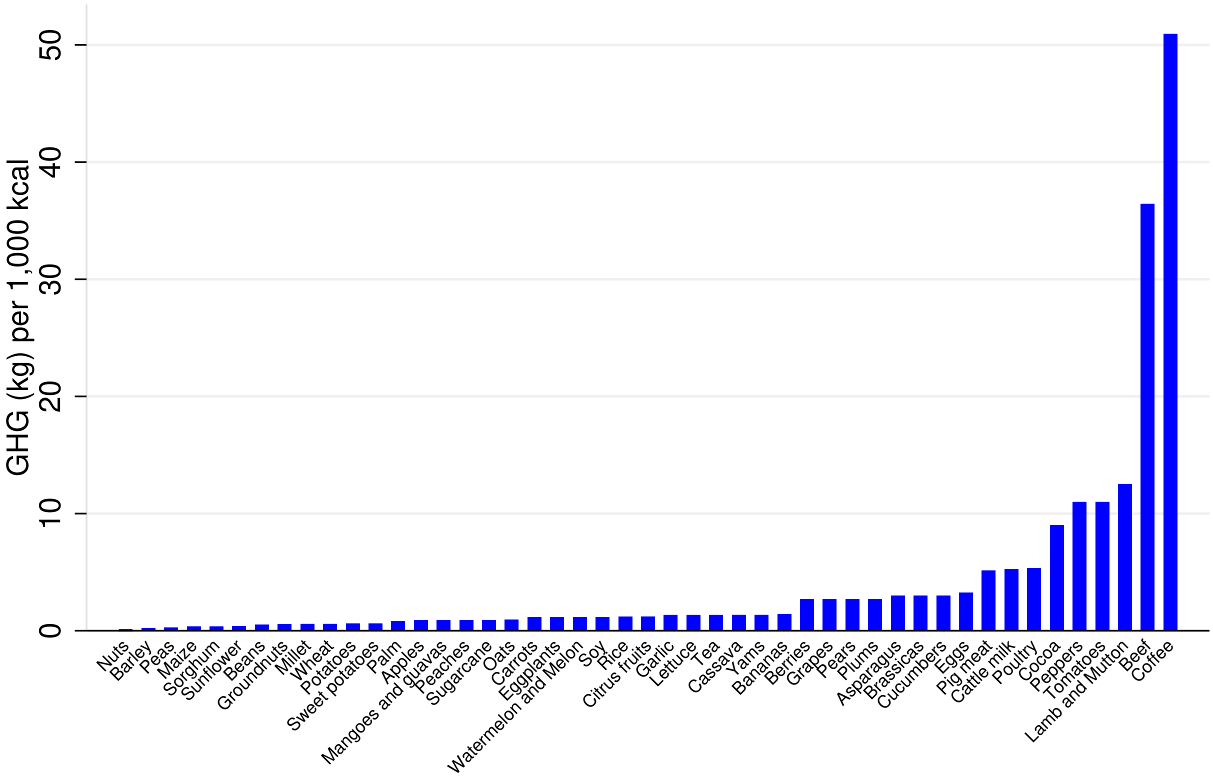
Notes: This table shows the impact of GHG emissions in different counterfactuals across the quartiles of GDP per capita in the baseline. q1 represents the bottom quartile in terms of GDP per capita and q4 the upper quartile. Every entry represents the change in average welfare within that quartile relative to the baseline.

Table O.4: GHG Emissions from Food Production Impact across Quartiles of GDP per capita

Counterfactual	q1 (1)	q2 (2)	q3 (3)	q4 (4)
TFP growth	7.8	6.3	6.4	3.8
No beef	-15.9	-13.3	-31.1	-18.6
Vegetarian	-28.2	-15.6	-37.3	-32.3
Eat local	-41.1	5.1	-21.5	0.4

Notes: This table shows the impact on GHG emissions in different counterfactuals across the quartiles of GDP per capita in the baseline. q1 represents the bottom quartile in terms of GDP per capita and q4 the upper quartile. Every entry represents the change in total emissions within that quartile relative to the baseline.

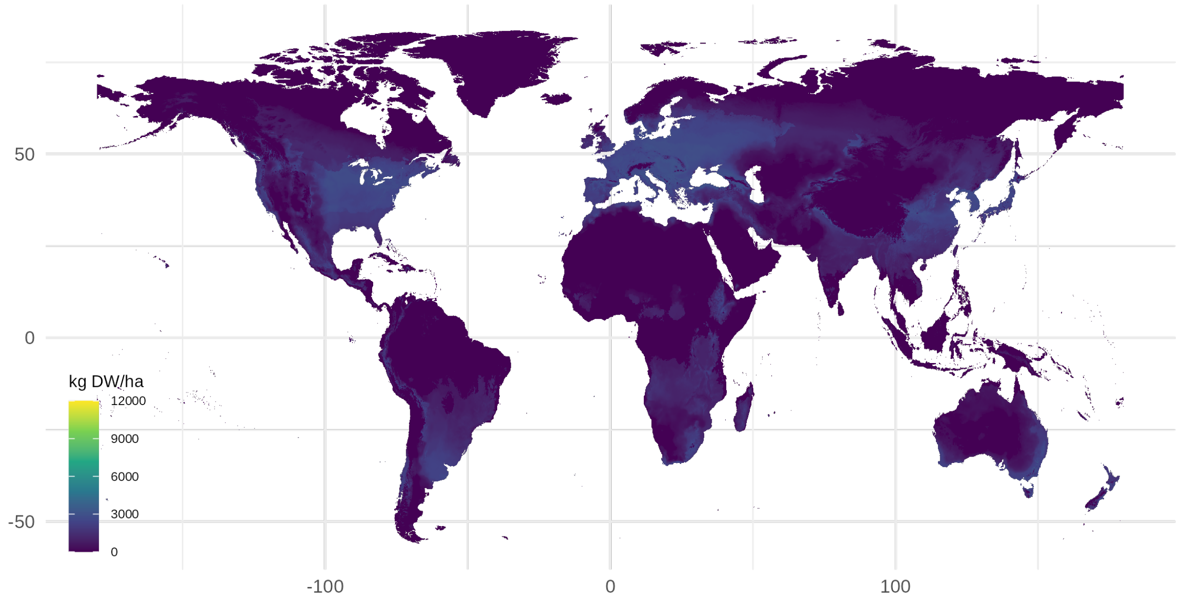
Figure O.1: GHG emissions per kilocalorie across food products



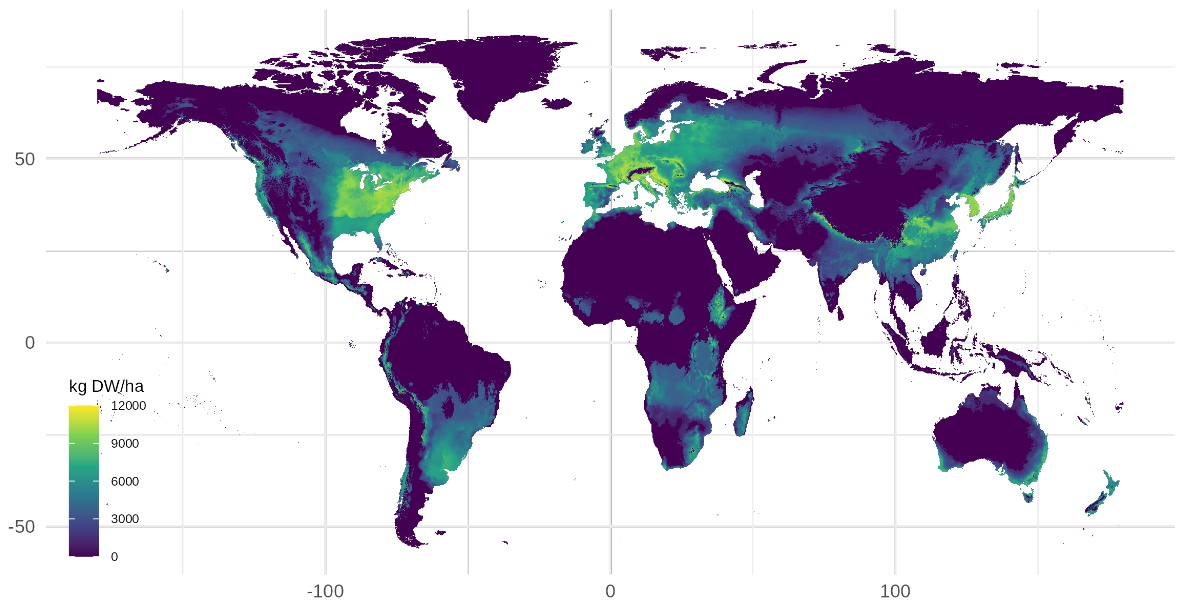
Notes: This figure shows the average global GHG emissions in CO2 equivalent of each food product in our data. We gather these measures based on information on GHG emissions by food product from Poore and Nemecek (2018), and build a crosswalk between the food products available in their dataset and our final data.

Figure O.2: Potential Yield Data (FAO-GAEZ)

(a) Wheat - Low Yield

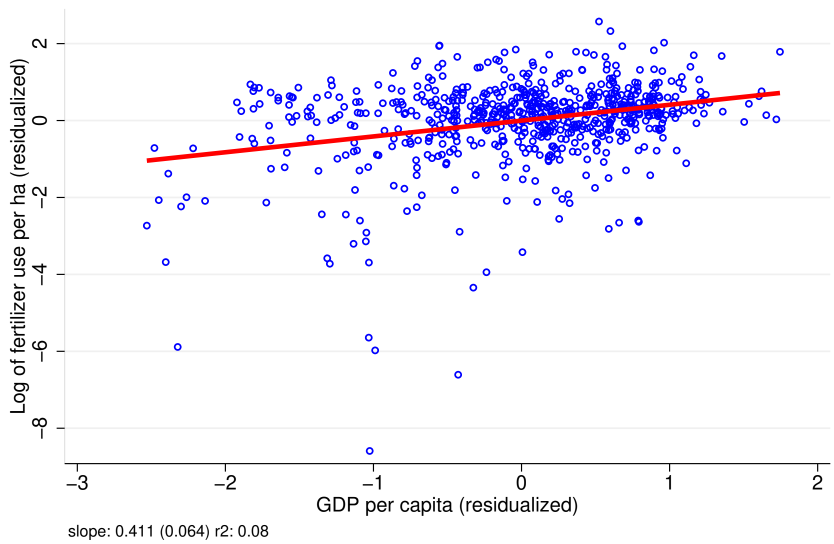


(b) Wheat - High Yield



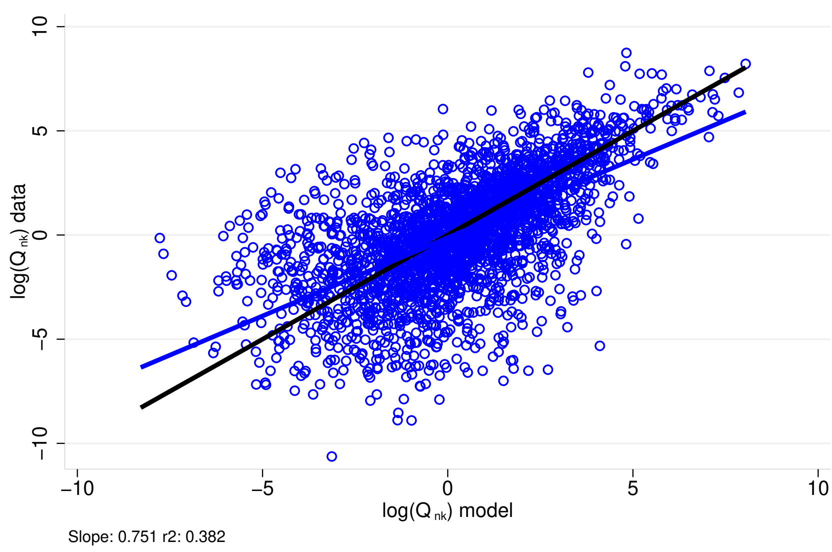
Notes: This figure shows distribution of potential yields across grid-cells. Panel (a) shows the potential yield for the low-input technology, which corresponds to traditional methods of production with minimal use of intermediate inputs. Panel (b) shows the potential yield for high-input technology, which corresponds to modern methods of production.

Figure O.3: Fertilizer use per hectare (within crop variation)



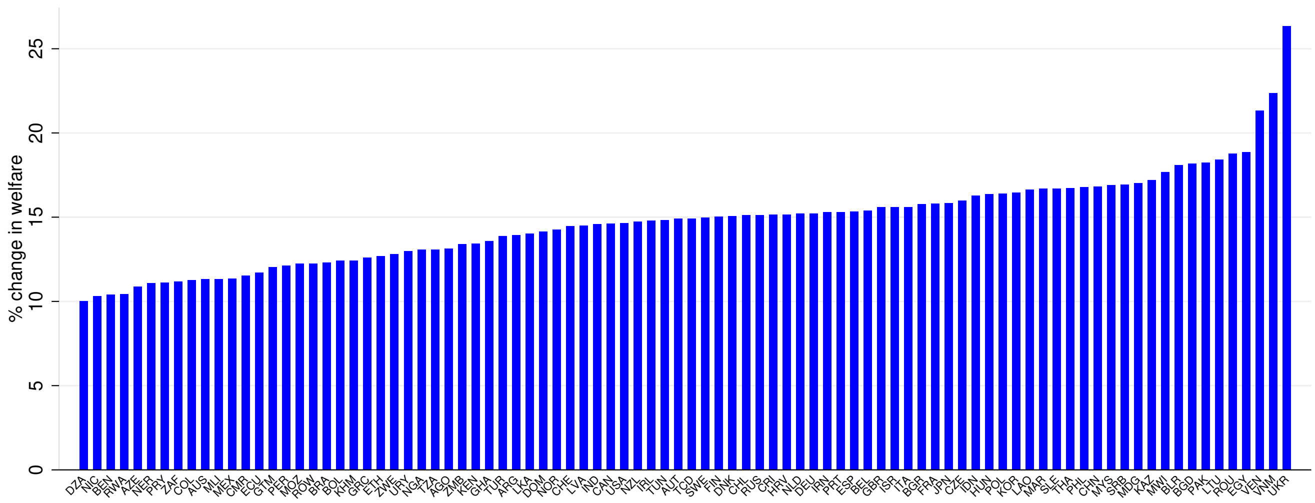
Notes: Logged fertilizer use per hectare in each crop and country against logged country GDP, after residualizing the values based on crop fixed effects — i.e., we run $y_{ik} = \alpha_k + \epsilon_{ik}$ and plot $\widehat{e}_{ik}$ where y_{ik} is log fertilizer use or log GDP. Data from the International Fertilizer Association (IFA-STAT), procuced by Ludemann et al. (2022).

Figure O.4: Fit of the model: production quantities



Notes: Each point in the figure represents a crop-country pair. We divide all quantities by the average quantity within a food product. On the y-axis we have the quantities predicted by the model using the FAO-GAEZ data. On the x-axis we have the actual quantities given by the FAO-STAT information. Black line shows the 45 degree line and the blue line the best linear fit.

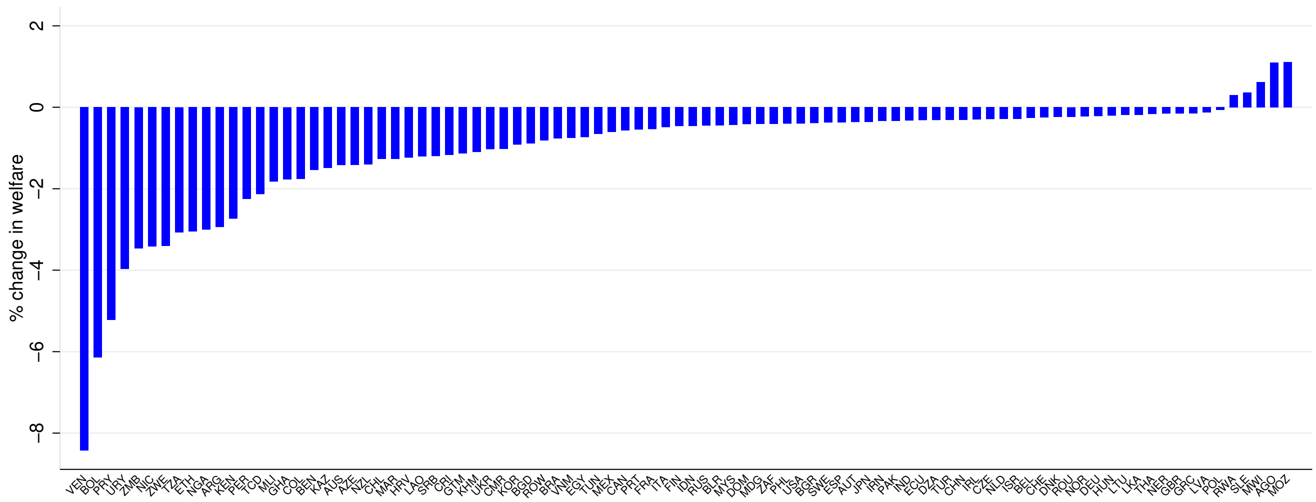
Figure O.5: Welfare Impact across Countries of TFP Growth



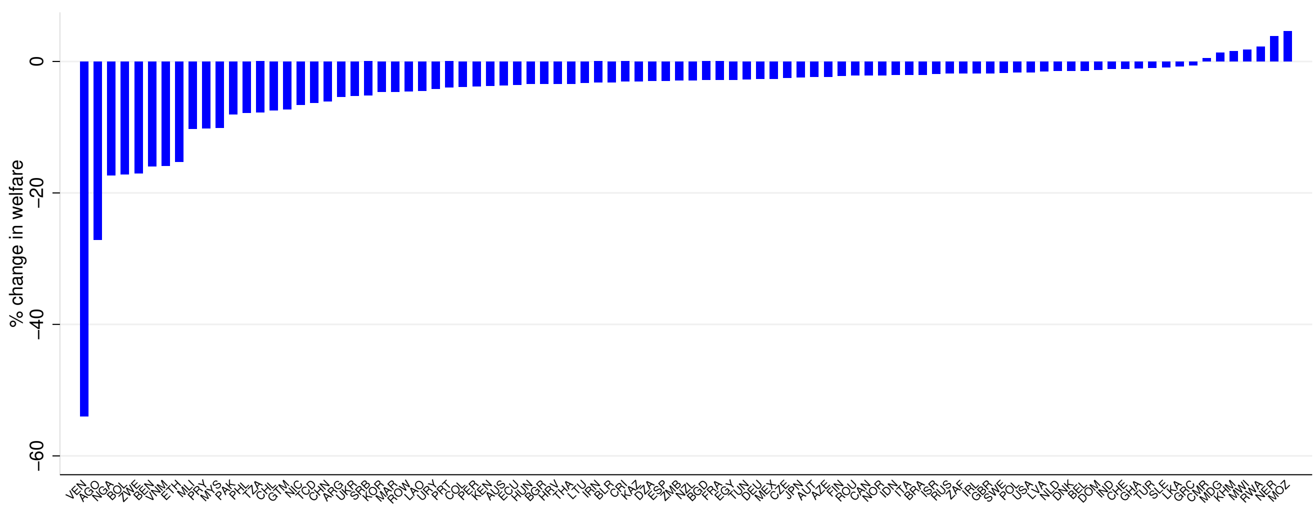
Notes: This figure shows the full distribution of the changes in welfare in each counterfactual in which the entire world's productivity increases by 10 percent in modern agriculture, non-agriculture and agricultural inputs.

Figure O.6: Welfare Impact across Countries in Diet Counterfactuals

(a) No Beef

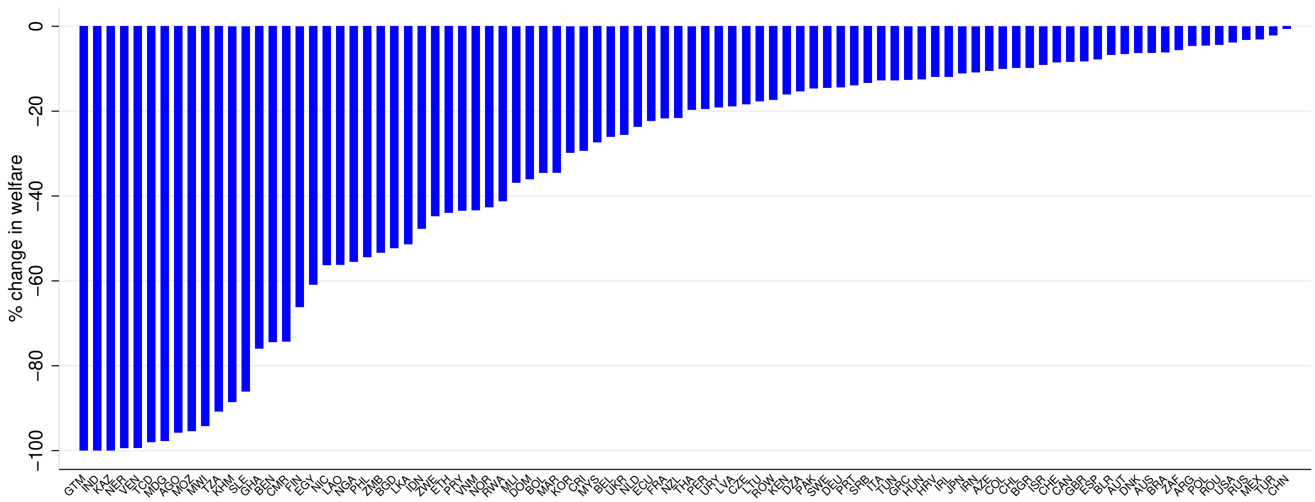


(b) Vegetarian



Notes: This figure shows the full distribution of the changes in welfare in each counterfactual in which we restrict the consumption of meat products. Panel (a) shows the impact of banning the consumption of bovine meat. Panel (b) shows the impact of banning the consumption of bovine meat, lamb, chicken, and pork.

Figure O.7: Welfare Impact across Countries of Eating Locally



Notes: This figure shows the full distribution of the changes in welfare in each counterfactual in which we restrict agricultural trade. Specifically, we increase agricultural trade costs by 30 percent, which is consistent with the reductions in global trade costs in recent decades. We drop Nepal, which is an outlier in the figure.

Appendix References

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