Diet, Economic Development and Climate Change

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PRELIMINARY

Abstract

This paper studies the impact of economic development on greenhouse gas emissions (GHG) from food production. We first 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 higher levels of GHG emissions. We incorporate these two mechanisms in a quantitative, general equilibrium framework by featuring, on the demand side, different income elasticities across food products and, on the supply side, multiple agricultural technologies, with crops and technologies being heterogeneous in their greenhouse emissions. We provide an approach for the estimation of income elasticities that sidesteps the need for price data by exploiting the model's open economy structure. Using the quantified model, we first find that about two thirds of the observed correlation between emissions and income is due to intrinsic preferences for diet, suggesting that the effect of economic growth on emissions will be less than the raw data would suggest. Second, we conduct a host of policy counterfactuals related to future economic growth, sustainable diet policies and trade policies, all of which have large interest in the literature and from the public more generally.

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 emissions from food production will catch up to the emissions from developed countries, exacerbating global climate change.

Several factors, however, contribute to the higher agricultural emissions in richer countries. Some of these factors might worsen with the process of economic development, such as the nutrition transition—the shift from cereal dominance to meats, fruits and vegetables as countries enrichen (Subramanian and Deaton, 1996; Deaton and Drèze, 2009)—and agricultural modernization—the increase in the use of intermediate inputs such as fertilizers and machinery (Johnston and Mellor, 1961; Schultz et al., 1968; Gollin et al., 2007; Farrokhi and Pellegrina, 2023). Other factors, such as variation in intrinsic preferences in diet, the patterns of comparative advantage in specific crops, or the geographic location of the country, may persist regardless of economic growth. Understanding the role of economic development on food emissions demands a framework that allows one to separate the influence of these different factors.

This paper studies the relationship between diet and agricultural emissions, and how this is transformed by economic development. We develop a quantitative, multi-country, general equilibrium model that incorporates the aforementioned factors. To quantify our model, we bring together several data sources, resulting in a rich, cross-country dataset with information on calorie consumption and GHG emissions (in tons of CO2 equivalent) from food production. In addition, we provide a new approach for the estimation of income elasticities that sidesteps the need for price data by exploiting the model's open economy structure. We then use the quantified model to decompose the contribution of economic development on the agricultural emissions across countries, and to simulate counterfactuals to evaluate the global impact of economic growth and of sustainability policies associated with food emissions.

We begin 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 calorie* and *per capita* from food consumption increase strongly with GDP per capita. Third, food products with higher levels of GHG emissions per calorie have higher income elasticities, indicating that as countries become wealthier, their diets shift towards more environmentally harmful food 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 crop* variation, in contrast to the *between crop* variation in pattern three, highlights the environmental implications of agricultural modernization.

We construct our model to rationalize 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 crop to plant and the amount of GHG-intense, intermediate input usage. As such, cross country differences in GHG emissions from agriculture stem from both differences in diet patterns, due to differences GHG emissions by food product, and from differences in production methods, due to the adoption of technologies with different input use levels. We provide a first order approximation result that highlights the different mechanisms driving the relationship between country-level emissions and economic growth.

We develop an estimation strategy of the income elasticities based on a linear regression, generalizing the method used in the literature —e.g., Comin et al. (2021)— to the non-nested CES version and to an open-economy model. Notably, we show that, unlike in the closed-economy version of the estimation of these preferences, price data is not needed for estimation when we estimate the model in an open economy. Specifically, we show how trade shares can be used to construct a sufficient statistic for the prices experienced by a representative consumer in that country. We estimate the technological parameters governing the GHG emissions by crop and country using information on GHG emissions by crop and GHG emissions across countries. Our quantified model closely matches numerous key relationships between GHG emissions, economic development and agricultural technology use in the data.

We first use the quantified model to understand the causal drivers of the observed, strongly increasing relationship between food GHG emissions and income across countries. This is critical for understanding the implications of economic growth for emissions and the appropriate policy response. We find that about two-thirds of the correlation is driven by

[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.

intrinsic diet preferences (reflecting for example culture or demographics), rather than income. This reveals that the effect of economic growth on emissions would be less than the raw data would suggest.

We second use the quantified model to conduct a host of policy counterfactuals related to future economic growth, sustainable diet policies and trade policies, all of which have a lot of interest in the literature and the public at large. For each counterfactual, we present the effect on welfare and emissions, and decompose the latter to understand the channels driving the change, such as due to the nutrition transition, agricultural modernization, and general equilibrium effects. The results and discussion of this exercise are still preliminary.

The outline of the paper is as follows. We first review the literature in the remainder of this section. In section 2, we describe our data and present the empirical patterns. In section 3, we present our quantitative model. In section 4, we quantify the model. In section 5, we present the results from our quantitative exercises. In section 6, we conclude.

Related Literature. This paper contributes to growing research on climate change using quantitative spatial models (see Desmet and Rossi-Hansberg, 2024 for a survey). Several recent papers have used these models to evaluate the impact of climate change on economic activity (Balboni, 2019; Bilal and Rossi-Hansberg, 2023; Burzyński et al., 2022; Cruz and Rossi-Hansberg, 2024; Desmet et al., 2018) or to evaluate the role of policy in reducing GHG emissions (Farrokhi and Lashkaripour, 2021; Conte et al., 2022). Conversely, and similar to us, Caron and Fally (2022) analyze the effect of income growth on GHG emissions. They also use a non-homothetic, spatial model, but their focus is not on agriculture, and their work is silent on the nutrition transition and agricultural modernization.

Focusing on the agricultural sector, Conte et al. (2021); Nath (2022); Costinot et al. (2016); Gouel and Laborde (2021) analyze the effect of climate change on agricultural specialization and reallocation between sectors. Dominguez-Iino (2021); Farrokhi et al. (2023); Hsiao (2021) study the impact of trade and tax policies on forest area and the implications to CO2 emissions. We innovate in this broad literature by assessing the environmental implications of changes in diet and agricultural modernization.

Our paper speaks to 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). We uncover the environmental implications of this phenomenon and bring a quantitative model to study it.

Lastly, we contribute to the extensive literature in environmental science evaluating the

impact of diet on emissions (Wallén et al., 2004; Carlsson-Kanyama and González, 2009; Hoolohan et al., 2013; Perignon et al., 2017; Hale et al., 2024). Our main contribution is to bring an economic model that accounts for different forms of economic adjustments, in particular incorporating the resulting changes in production costs and price that changes in food demand will induce. Abstracting from supply side responses seem highly consequential for the estimated effects of diet on emissions, as presumably production becomes more costly as aggregate demand is shifted by changes in diet.

2 Data and Empirical Patterns

Our dataset contains 90 countries, plus a representative country for the rest of the world, and 47 food products listed in Appendix Table XXX. For each country, we have information on calories intake by food product, CO2 emissions from food production and consumption, bilateral trade flows and gross output by sector. Moreover, for each food product, we construct grid-level information on potential yields for more than 1 million grids across the Earth.[2] For a subset of countries, we collect household level data with information on consumption. This section briefly describes our data and presents empirical patterns relating calories consumed and produced, CO2 emissions and economic development. Appendix OA describes the data in detail.

2.1 Data

GHG emissions from agriculture. 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 (in tons of CO2 equivalent) by food product. Specifically, the authors collect information from more than 1500 studies to construct measures of GHG emissions for more than 80 food products, representing 90% of protein and calorie intake worldwide. They provide measures of the 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 consumed and bilateral trade flows.[3] Their data shows large variation in the GHG emissions per calorie across food products. For example, meat and coffee generates more

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

[3]See Appendix Table O.3 and O.4 for the crosswalk.

than 35 kilos of CO2 per 1000 kilocalories, whereas wheat and rye produce less than 5 kilos of CO2 per 1000 kilocalories — see Appendix Figure O.2.[4]

The second dataset is the Emissions Database of Global Atmospheric Research (EDGAR-FOOD), which is constructed by Crippa et al. (2021). This provides cross country-level information on CO2 emissions by stages of agricultural production — e.g., production, processing, and packaging. This dataset is designed to be consistent with the measures of CO2 emissions reported in the original EDGAR dataset, which contains information for all sectors in the economy, and with Food and Agriculture Organization Corporate Statistical Database (FAOSTAT), which we utilize for information on agricultural production and consumption. Relative to PN18, this dataset does not provide CO2 emissions by food product, but it provides measures of GHG emissions for a wider range of countries.

Trade and production of food products in calories and values. For calorie intake by country and food product, we collect data from the Food and Agriculture Organization (FAO) Food Balance Sheets (FBS). These data come from a special annual report produced by FAO since the 1960s that focuses on calories consumed by food product across countries We combine these data with information on CO2 emissions by food product from PN18, which allows us to construct a measure of GHG emissions implied from food consumption patterns. Specifically, we take a simple approach to construct our measure of GHG emissions from food consumption: we multiply the average GHG emissions by calories obtained in PN18 by the total calories consumed by food product collected by FBS.[5]

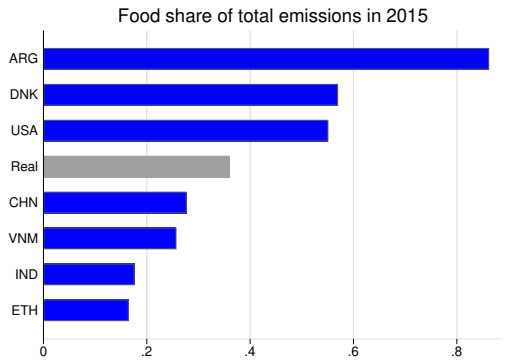
We also bring in data on bilateral trade flows and revenues by food product from FAO-STAT and data on value added by sector (agriculture, services and manufacturing) from the United Nations. Both of these datasets are measured in dollar values. We also collect data on fertilizer use per crop measured in tons, produced by Ludemann et al. (2022) based on the global reports from the International Fertilizer Association (IFA-STAT). Lastly, information on GDP per capita and total labor employment comes from the Penn World Tables.

[4]In addition, we collected data on CO2 emissions by stages of production from Emissions Database of Global Atmospheric Research (EDGAR-FOOD). This dataset provides cross-country measures the global GHG emissions from the agricultural sector, disaggregated by stages of production, such as packaging, retail, and production.. These data allow us to create, for each country, separate measures of CO2 emissions from farm production and from food processing. We plan to incorporate this dataset in the next iteration of our work. See Appendix Complementary Pattern OB.

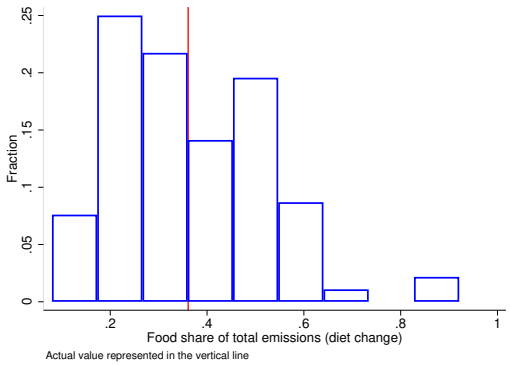
[5]This is an implied measure of CO2 emissions that does not take into account whether the food product that was consumed in a given country was produced with or without a CO2-intensive technology. Since the food products produced with different technologies are the same from the point of view of the consumer (and especially the data), we are unable to take that dimension into account.

Figure 1: Implied global GHG emissions from each countries' diet (2015)

(a) Selected Countries



(b) Distribution across countries



Notes: we calculate the change in food GHG emissions from changing the composition of global food composition to that of a particular country, while holding fixed total calories consumed. Data on emissions is from Poore and Nemecek (2018) and number of calories from FAO-STAT.

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. Among other uses, this data is employed in the construction of consumer price indexes.

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 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. Figure 2a 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.[6] Indeed, Figure 2b 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 (Figure 2a). The remainder is due to a compositional effect: richer economies consume calories from food products associated with higher GHG emissions per calorie. We see this in Figure 3c, 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.

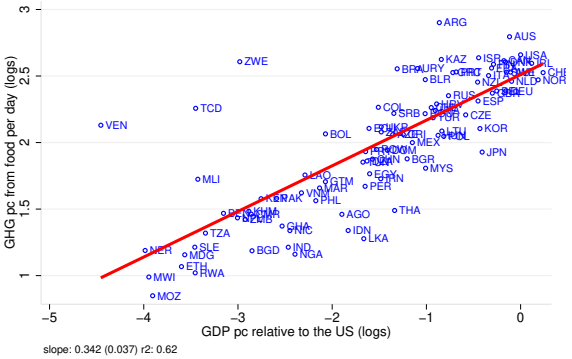
This decomposition reveals that the food products consumed in richer economies are associated with greater GHG emissions. In the next two empirical patterns, we provide evidence suggesting that the nutrition transition and agricultural modernization help explain this relationship.

Empirical Pattern 3. Agricultural goods with higher levels of GHG emissions have higher income elasticities. The first mechanism regards the environmental implication of the nutrition transition (Tilman et al., 2011). This 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

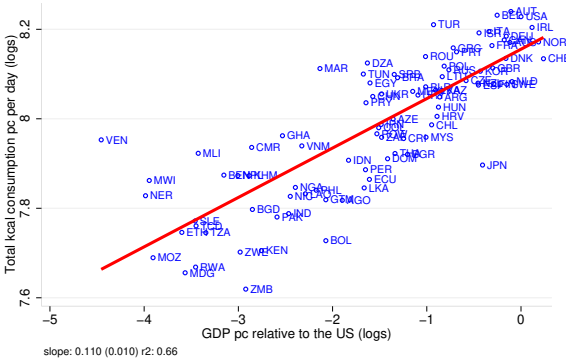
[6]The estimated relationship is approximately log-linear across different levels of economic development. One could hypothesize an inverse-U shape — the Environmental Kuznets Curve — reflecting a decline in emissions as countries get very rich, perhaps due to the adoption of more sustainable diets or governmental policies. We find, however, no evidence of this phenomenon, like much of the literature (Dinda, 2004). Appendix Figure O.3 shows that even within country, over time, we find no evidence.

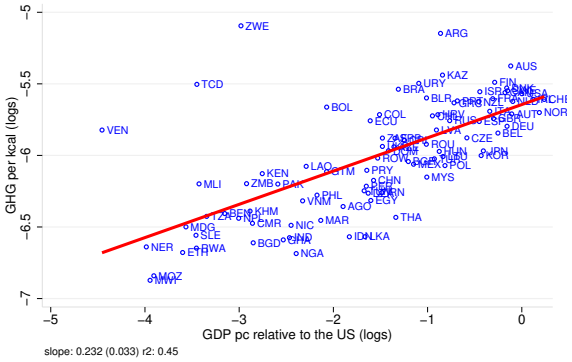
Figure 2: GHG Emissions from Food Consumption, Calories Intake, and GDP per capita

(a) Food GHG per capita



(b) Calories per capita





(c) Food GHG per calorie

Notes: This figure shows the relationship between GHG emissions (measured in tons of CO2 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.

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 the following equation:

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

where $E_{j,k,t}$ is country j log expenditure on good k from all countries ("absorption") in period t.[7] The coefficient, α_k, on log GDP per capita in country j, $\text{GDPpc}_{j,t}$, is the income elasticity

[7] In this early version of the draft, we only have one time period, therefore the fixed effect specification is simply $\varphi_j + \gamma_k$.

Table 1: Income Elasticity and GHG Emissions per calorie

	(1)	(2)
log (CO2pk) × log (GDPpc)	0.181***	0.168**
	(0.055)	(0.065)
Observations	4110	3837
Adjusted R^2	0.636	0.626
Excluding meat products	-	Y

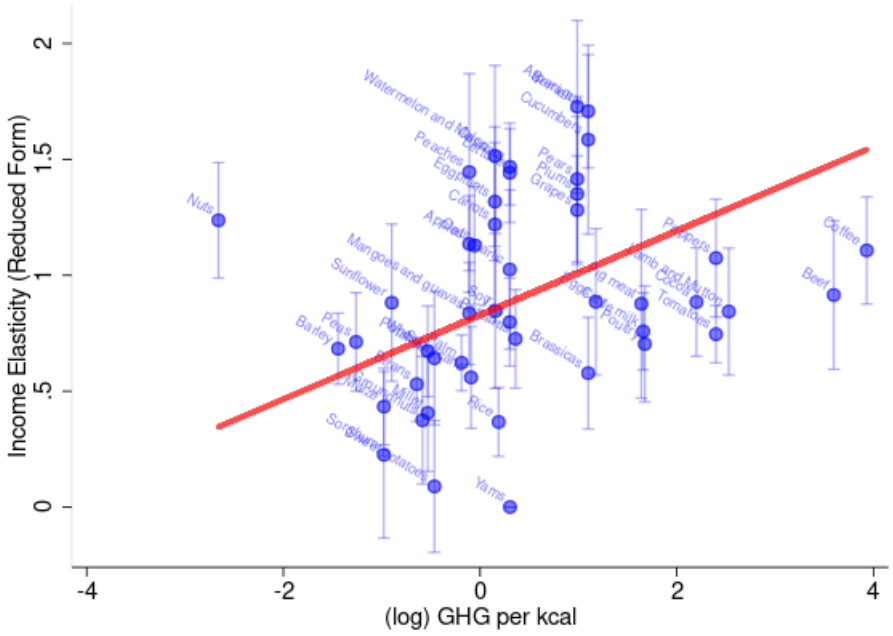
Twoway (product, country) cluster robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of good k. We parameterize this as a function of CO2 emissions per kilo-calorie of good k, $\delta_k = \tilde{\delta} \cdot \text{GHGpk}_k$, in order 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 demand that are correlated with GDPpc. The fixed effects go some way to ensuring this. The country-good fixed effect, $\varphi_{j,k}$, controls for time-invariant determinants, such as geographical proximity to productive producers, or a country's secular tastes for particular diets. The good-time fixed effect $\gamma_{k,t}$ captures any global factors, such due to good-specific technological progress or effects of climate change. There may be remaining factors of concern (such as regional technological change raising j's GDP and lowering prices of its nearby import partners). 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 endogeneity due to prices.

Table 1 reports our results for $\tilde{\delta}$. Column (1) is the baseline, while column (2) excludes meat products ("Beef", "Goat sheep lamb", "Pig meat", "Poultry") to check if these are driving our results. 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. 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 positive correlation between income elasticities and GHG emissions per capita. Our model in section 3 incorporates the influence of nonhomothetic preferences on GHG emissions.

Figure 3: Income Elasticities and GHG emissions per calorie



Notes: Error bars show 95% confidence intervals. The linear relation shown is using the slope estimate from table 1, column (1).

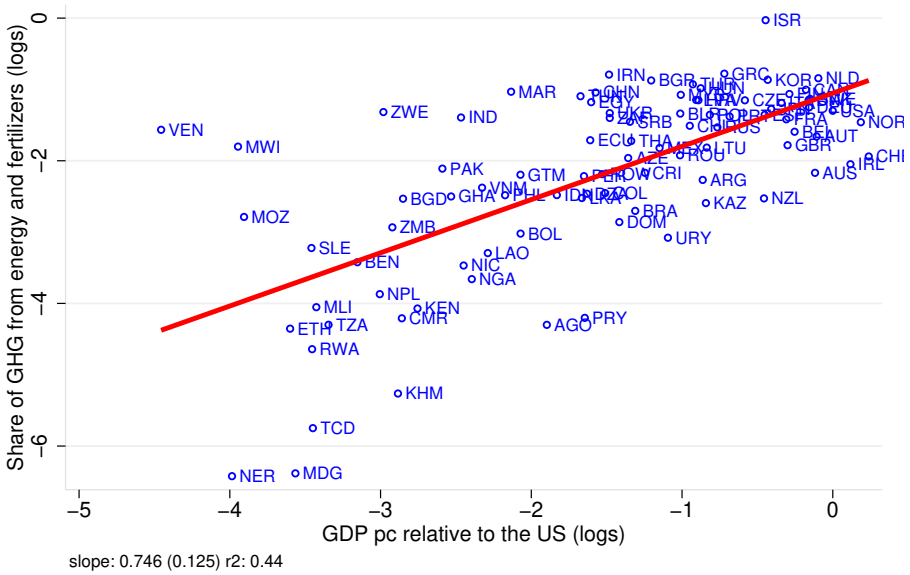
Household Level Estimates. Appendix Section OB presents analogous estimates of the correlation between income elasticities by food product and the CO2 emissions per product using household level data from Brazil. Our qualitative findings are the same as the ones using the country-level data: Food products with higher income elasticity are more harmful for the environment and the correlation persists after controlling for a host of fixed effects and proxies for food prices.

Empirical Pattern 4. GHG emissions from the use of modern agricultural technologies increase with GDP per capita. The second mechanism regards the environmental implication of agricultural modernization. This 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.[8] 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.[9] Our model in Section 3 incorporates the influence of technological choices

[8]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).

[9]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, Ap-

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



Notes: Log GHG emissions from the use of fertilizers and energy in farm production at the country level from FAO-STAT against log GDP per capita.

on GHG emissions.

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, based on a simplified version of the model, for the impact of economic development on GHG emissions through agriculture.

pendix Figure O.5 shows that the amount of fertilizer use per unit of land is markdly increasing with GDP per capita. This suggests that even for the same crop, richer countries use more fertilizer-intense technologies.

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 two sectors $s \in \{NA, A\} \equiv \mathcal{S}$, representing agriculture and non-agriculture. Each sector is composed of multiple goods, indexed by $k \in \mathcal{K}_s$, where $\mathcal{K}_s$ is the set of goods that belong to sector s, and $\mathcal{K} \equiv \{\mathcal{K}_s\}_{s\in\mathcal{S}}$.[10] Within the agricultural sector, each good represents different agricultural 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 a nested non-homothetic CES with a three tier structure.[11] In the upper tier, utility U_i is composed of sectoral goods $\tilde{C}_{i,s}$:

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

We have three sectors in our model: the agricultural sector, $s = A$, the agricultural input sector (representing machines and fertilizers), and the remainder of the economy (manufacturing and services). In the middle tier, sectoral goods $\tilde{C}_{i,s}$ are composed of multiple goods $C_{i,k}$:

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

In the agricultural sector, these goods correspond to crops. For the other sectors, we assume only a single good in the middle tier. In the lower tier, goods $C_{i,k}$ are composed of multiple varieties of goods $c_{ji,k}$

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

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

[10] In this section, we assume two sectors to simplify notation. The essential mechanisms are unaffected. In the quantitative model, we split the non-agricultural sector into manufacturing and services.

[11] See Duernecker et al. (2024) and Hoelzlein (2019) for recent applications of the nested non-homothetic CES preferences.

[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.

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 controling 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 given by

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

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 of the representative consumer is solved implicitly by[14]

$$U_i = \frac{E_i}{P_i}. \tag{10}$$

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.

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

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

Each field has a continuum of plots ℓ. In each plot, agricultural producers choose which crop k to produce, and with which technology τ to produce that crop. The production technology is

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

where $z_{i,k\tau}^{f}(\ell)$ 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 $z_{i,k\tau}^{L}(\ell)$ is drawn from a generalized Frechet distribution with productivity shifters $T_{i,k\tau}^{f}$ and dispersion parameters θ_1 for 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

$$\alpha_{i,k}^{f} = \frac{\left(H_{i,k}^{f}\right)^{\theta_1}}{\sum_{k \in \mathcal{K}_A} \left(H_{i,k}^{f}\right)^{\theta_1}} \tag{12}$$

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

$$\alpha_{i,k\tau}^{f} = \frac{\left(T_{i,k\tau}^{f} h_{i,k\tau}\right)^{\theta_2}}{\left(H_{i,k}^{f}\right)^{\theta_2}}, \tag{13}$$

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

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

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

$$Q_{i,k\tau}^{f} = L_{i}^{f}\left(\gamma_{k\tau}^{L}\right)^{-1}\frac{h_{i,k\tau}}{p_{i,k}^{F}}T_{i,k\tau}^{f}\left(\alpha_{i,k}^{f}\right)^{\frac{\theta_1-1}{\theta_1}}\left(\alpha_{i,k\tau}^{f}\right)^{\frac{\theta_2-1}{\theta_2}}. \tag{15}$$

Total sales at the field level is given by

$$Y_{i,k\tau}^{f} = p_{i,k}^{F}Q_{i,k\tau}^{f}, \tag{16}$$

aggregate revenues of country i using technology τ by

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

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

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

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 Ω be the matrix of bilateral trade cost between any two countries j and i in good k and $p_{i,k}^{F}$ be the producer price at location i — i.e., the farm-gate price for agricultural producers. $p_{ji,k}$ is therefore given by

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

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

$$E_i = w_i N_i + \sum_{k\in\{A\}}\sum_{\tau\in\{0,1\}} \gamma_{k\tau}^{L} Y_{i,k\tau}. \tag{21}$$

Second, expenditure of country i on goods k from country i 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 Ω, 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 model the GHG emissions from agricultural production as follows. The total emissions from food production in country i is assumed to be

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

where $Q^C_{i,k\tau}$ is the calorie equivalent of production quantity $Q_{i,k\tau} \equiv \sum_{f \in \mathcal{F}_i} Q^f_{i,k\tau}$, which in turn is is total production of crop k using technology τ in country i.[15] $\varphi_{k\tau}$ is the per-calorie GHG emissions from the production of agricultural good k using technology τ. We model

[15] We use standard measures of calories per kg from the literature to implement this transformation.

the emissions this way due to its simplicity and versatility. The parameter φ_{kt} is a reduced form measure capturing all sources of emissions associated with the production of a single calorie. This can originate from the intermediate inputs used in production that we explicitly model, such as fertilizers and machines, from inputs we do not model, such as energy usage and land use change, and from the production process itself, such as the release of methane from cattle ranching.[16]

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 (see appendix section OC.2.1 for the derivation)

$$\frac{\partial \ln \beta_{i,k}}{\partial \ln E_i} = \frac{1-\varsigma}{1-\varsigma+\bar{\epsilon}_i} \cdot \left(\epsilon_k - \tilde{\epsilon}_{i,s(k)}\right) \tag{27}$$

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 nonhomothetic 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, for any two products k, k' in the same sector, equation (27) 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. Insight into the dependence in equation (27) of the income elasticity on the remaining parameters

[16] 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.

of the model can be had by looking at its derivation. Using equation (7),

$$\frac{\partial \ln \beta_{i,k}}{\partial \ln E_i} = \epsilon_k \underbrace{\left(1 - \frac{\partial \ln P_i}{\partial \ln E_i}\right)}_{=\frac{\partial \ln U_i}{\partial \ln E_i}, \text{ using eq (10)}} - (1-\varsigma)\frac{\partial \ln \tilde{p}_{i,s(k)}}{\partial \ln E_i} \tag{28}$$

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 nonhomothetic. This is modulated by the parameter ϵ_k and is the first term in equation (28). Utility is equal to real expenditure, $U_i = E_i/P_i$, thus this channel incorporates the resulting change in the overall price index P_i due to the nonhomothetic adjustment of the overall consumption basket as utility changes. The second channel, reflected by the second term in equation (28), arises due to the nonhomothetic 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

$$\frac{\partial \ln \tilde{\beta}_{i,s}}{\partial \ln E_i} = \frac{1-\sigma}{1-\varsigma+\bar{\epsilon}_i} \cdot (\tilde{\epsilon}_{i,s} - \bar{\epsilon}_i) \tag{29}$$

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, for any two sectors s, s'

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

with the left inequality strict if the right inequality is strict. That is, the sectors inherit their nonhomotheticity 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

$$\frac{\partial \ln (p_{i,k} C_{i,k})}{\partial \ln E_i} = \underbrace{\frac{\partial \ln \beta_{i,k}}{\partial \ln E_i}}_{\text{Reallocation between } k \text{ within } s(k)} + \underbrace{\frac{\partial \ln \tilde{\beta}_{i,s(k)}}{\partial \ln E_i}}_{\text{Reallocation between } s} + \underbrace{1}_{\text{Scale}} \tag{30}$$

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

$$\delta_k = \mathbb{E}_{i|k}\left[\frac{\partial \ln\left(p_{i,k}C_{i,k}\right)}{\partial \ln E_i}\right] \tag{31}$$

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 (27) and (30) into equation (31), giving

$$\frac{\delta_k - \delta_{k'}}{\delta_k - \delta_{k''}} = \frac{\epsilon_k - \epsilon_{k'}}{\epsilon_k - \epsilon_{k''}} \tag{32}$$

for products k, k', k'' all in the same sector. See appendix section OC.2.2 for the derivation.

3.5 Economic Development and Emissions

To gain intuition on the model mechanisms relating the change in GHG emissions 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, G_i, is

$$\begin{aligned}
\frac{\mathrm{d}\ln G_i}{\mathrm{d}\ln T_{i,NA}} = &\sum_{k\in\mathcal{K}_A}\sum_{\tau\in\{0,1\}} \frac{\varphi_{k\tau}Q^C_{i,k\tau}}{G_i}\cdot\frac{\partial \ln \frac{Q_{i,k\tau}}{Q_{i,k}}}{\partial \ln w_i}\cdot\frac{\mathrm{d}\ln w_i}{\mathrm{d}\ln T_{i,NA}} && \text{Agricultural modernization if } > 0\\
&+\sum_{j\in\mathcal{I}}\sum_{k\in\mathcal{K}_A}\frac{X_{ij,k}}{Y_{i,k}}\cdot\frac{\sum_{\tau\in\{0,1\}}\varphi_{k\tau}Q^C_{i,k\tau}}{G_i}\cdot\frac{\partial\ln\beta_{j,k}}{\partial\ln E_j}\cdot\frac{\mathrm{d}\ln E_j}{\mathrm{d}\ln T_{i,NA}} && \text{Nutrition transition if } > 0\\
&+\sum_{j\in\mathcal{I}}\frac{\sum_{k\in\mathcal{K}_A}\frac{X_{ij,k}}{Y_{i,k}}\sum_{\tau\in\{0,1\}}\varphi_{k\tau}Q^C_{i,k\tau}}{G_i}\cdot\frac{\partial\ln\left(\tilde{p}_{j,A}\tilde{C}_{j,A}\right)}{\partial\ln E_j}\cdot\frac{\mathrm{d}\ln E_j}{\mathrm{d}\ln T_{i,NA}} && \text{Scale effect}\\
&+\sum_{k\in\mathcal{K}_A}\sum_{\tau\in\{0,1\}}\frac{\varphi_{k\tau}Q^C_{i,k\tau}}{G_i}\cdot\frac{\partial\ln Q_{i,k\tau}}{\partial\ln \mathbf{p}'}\cdot\frac{\mathrm{d}\ln \mathbf{p}}{\mathrm{d}\ln T_{i,NA}} && \text{Price effect}
\end{aligned} \tag{33}$$

where $Q^C_{i,k} \equiv \sum_{\tau\in\{0,1\}} Q^C_{i,k\tau}$ is total calories from production of crop k in country i. See appendix section OC.4 for the derivation. 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.

Agricultural modernization manifests 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, $\frac{\varphi_{k\tau} Q^C_{i,k\tau}}{G_i}$. This is the empirically relevant case in the model because the modern technology has greater emissions and is labor saving, $\frac{\gamma^N_{k1}}{\gamma^L_{k1}} < \frac{\gamma^N_{k0}}{\gamma^L_{k0}}$ (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

$$\frac{\partial \ln \frac{Q_{i,k\tau}}{Q_{i,k}}}{\partial \ln w_i} = \theta_2 \frac{Q_{i,k,1-\tau}}{Q_{i,k}} \left(\frac{\gamma^N_{k,1-\tau}}{\gamma^L_{k,1-\tau}} - \frac{\gamma^N_{k\tau}}{\gamma^L_{k\tau}} \right) \tag{34}$$

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

The nutrition transition manifests 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), $\frac{\sum_{\tau \in \{0,1\}} \varphi_{k\tau} Q^C_{i,k\tau}}{G_i}$. Ignoring the effect of the domestic trade share, $\frac{X_{ii,k}}{Y_{i,k}}$, for the moment, this is the empirically relevant case in the model 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 (27), 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. This is a manifestation of the pollution haven hypothesis (Copeland and Taylor, 2004). 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 method 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 Method

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 (η, ς, σ) equal to values in the literature. Second, we calibrate the technology parameters and shifters: 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 preference shifters ($\tilde{a}_{i,s}$, $a_{i,k}$, and $a_{ij,k}$), while setting the crop-technology elasticities (θ_1 and θ_2) to values in the literature. Third, with the baseline model calibrated and simulated, we estimate the GHG emissions per crop and technology, $\varphi_{k\tau}$.

4.1.1 Step 1: Income Elasticities and Substitution Parameters

Our method to estimate the income elasticity parameters generalizes Comin et al. (2021) to *nested* nonhomothetic CES preferences and to an open-economy. As in their case, we utilize the implicit Marshallian demand for identification.[17] 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.[18] We briefly explain the estimation steps below, providing a full derivation in Appendix Section OD.1.

The first step is to use a base good $k^* \in \mathcal{K}$, which will be manufacturing in our setting, to substitute out the upper and middle level price indices, $P_i, \tilde{p}_{i,s}$. To substitute out the overall

[17] 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.

[18] Comin et al. (2021) and Caron and Fally (2022) provide approximate methods for the non-nested nonhomothetic CES that do not require price data: they impose additional assumptions that are only approximately true in reality. Comin et al. (2021) assume prices don't 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.

Table 2: Parameter Values

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)	2
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	-
$a_{i,k}$	Demand shifters of goods	Good-level expenditure shares	-
$\tilde{a}_{i,s}$	Demand shifters of sectors	Sector-level expenditure shares	-
Supply-side			
θ_1	Productivity dispersion between crops	Farrokhi and Pellegrina (2023)	1.5
θ_2	Productivity dispersion between technologies	Farrokhi and Pellegrina (2023)	4.5
$a_{i,k\tau}^f$	Crop-technology productivity shifter	Potential yields from FAO-GAEZ	-
$\gamma_{k\tau}^N, \gamma_{k\tau}^L, \gamma_k^M, \gamma_k^{j,M}$	Factor and input shares	USDA & Cross-country input cost share	-
GHG emissions			
φ_k	Emissions from good k	(Poore and Nemecek, 2018)	-
φ_τ	Global emissions moments	EDGAR-FOOD	-

price index, P_i, rearrange demand for the sector of the base good, equation (8), to give

$$\begin{aligned} P_i^{1-\sigma} &= \frac{\tilde{a}_{i,s(k^*)}\tilde{p}_{i,s(k^*)}^{1-\sigma}}{\tilde{\beta}_{i,s(k^*)}} \\ &= \frac{\tilde{a}_{i,s(k^*)}\left(a_{i,k^*}U_i^{\epsilon_{k^*}}p_{i,k^*}^{1-\varsigma}\right)^{\frac{1-\sigma}{1-\varsigma}}}{\tilde{\beta}_{i,s(k^*)}} \\ &= \frac{\tilde{a}_{i,s(k^*)}a_{i,k^*}^{\frac{1-\sigma}{1-\varsigma}}p_{i,k^*}^{1-\sigma}}{\tilde{\beta}_{i,s(k^*)}} \end{aligned} \tag{35}$$

The second line used equation (9) and the fact that $s\left(k^*\right)$ in our model only has a single product, $\left|\mathcal{K}_{s(k^*)}\right| = 1$ (a sole manufacturing 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, $\forall s \in \mathcal{S}\backslash s\left(k^s\right) : p_{i,s}$, rearrange demand for those sectors, equation (8),

$$\tilde{p}_{i,s}^{1-\sigma} = \frac{\tilde{\beta}_{i,s}P_i^{1-\sigma}}{\tilde{a}_{i,s}} \tag{36}$$

Equations (35) and (36) provide expressions for $P_i, \tilde{p}_{i,s}$ that, conditional the expenditure shares, $\tilde{\beta}_{i,s}$, and (homothetic) 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.[19] Rearranging equation (6), inserting $p_{ji,k} = p_{j,k}^F d_{ji,k}$ from equation (20), taking logs, and summing over country i's import partners $j \in \mathcal{I}_{i,k}^{\neg 0}$, gives

$$(1-\eta)\ln p_{i,k} = \underbrace{-\frac{1}{N_{\mathcal{I}_{i,k}^{\neg 0}}}\sum_{j\in\mathcal{I}_{i,k}^{\neg 0}}\ln\beta_{ji,k}}_{\equiv\ln\hat{\beta}_{i,k}} + \underbrace{(1-\eta)\frac{1}{N_{\mathcal{I}_{i,k}^{\neg 0}}}\sum_{j\in\mathcal{I}_{i,k}^{\neg 0}}\ln p_{j,k}^F}_{\equiv\ln\hat{p}^F_{\mathcal{I}_{i,k}^{\neg 0},k}} + \underbrace{\frac{1}{N_{\mathcal{I}_{i,k}^{\neg 0}}}\sum_{j\in\mathcal{I}_{i,k}^{\neg 0}}\ln\left(a_{ji,k}\tau_{ji,k}^{1-\eta}\right)}_{\equiv 0} \tag{37}$$

$\mathcal{I}_{i,k}^{\neg 0}$ 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

[19] 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.

partners). Summing over this set is required to avoid log of zero in the summand.

$\hat{\beta}_{i,k}, \hat{p}^F_{\mathcal{I}^{\neg 0}_{i,k},k}$ are geometric averages of variety expenditure shares, $\beta_{ji,k}$, and production prices, $p^F_{j,k}$, across location i's import partners for product k. The third term in equation (37) is normalized to zero, without loss of generality[20].

The final step is to use equations (35), (36) and (37) to substitute out $\tilde{p}_{i,s}, P_i$ and $p_{i,k}$, respectively, in demand for good $k \neq k^*$, equation (7)

$$\ln \beta_{i,k} = \epsilon_k \ln E_i - \left(\frac{1-\varsigma}{1-\sigma}\right) \ln \tilde{\beta}_{i,s(k)} - \frac{1-\varsigma}{1-\eta} \ln \hat{\beta}_{i,k} + \frac{\epsilon_k + 1 - \varsigma}{1-\sigma} \ln \tilde{\beta}_{i,s(k^*)} + \frac{\epsilon_k + 1 - \varsigma}{1-\eta} \ln \hat{\beta}_{i,k^*}$$
$$+ \underbrace{(1-\varsigma) \ln \hat{p}^F_{\mathcal{I}^{\neg 0}_{i,k},k}}_{\left\{\mathcal{I}^{\neg 0}_{i,k},k\right\} \text{ FE}} + \underbrace{(\varsigma - 1 - \epsilon_k) \ln \hat{p}^F_{\mathcal{I}^{\neg 0}_{i,k^*},k^*}}_{\left\{\mathcal{I}^{\neg 0}_{i,k^*},k\right\} \text{ FE}} + \underbrace{\ln \left(\frac{a_{i,k} \tilde{a}_{i,s(k)}^{\frac{1-\varsigma}{1-\sigma}}}{a_{i,k^*}^{\frac{\epsilon_k+(1-\varsigma)}{1-\varsigma}} \tilde{a}_{i,s(k^*)}^{\frac{\epsilon_k+(1-\varsigma)}{1-\sigma}}} \right)}_{\text{residual}} \tag{38}$$

Equation (38) 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 expenditure, E_i, and expenditure shares, $\tilde{\beta}_{i,k}, \tilde{\beta}_{i,s(k)}, \hat{\beta}_{i,k}, \hat{\beta}_{i,k^*}$. Importantly, because the estimation equation only depends on averages of the production prices, $\hat{p}^F_{\mathcal{I}^{\neg 0}_{i,k},k}, \hat{p}^F_{\mathcal{I}^{\neg 0}_{i,k^*},k^*}$, these terms can be controlled for using appropriate fixed effects. For instance, the $\left\{\mathcal{I}^{\neg 0}_{i,k}, k\right\}$ 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, $\mathcal{I}^{\neg 0}_{i,k}$, 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. Thus, by utilizing variation across different countries purchasing said products, one candifference 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 to each price via its imports.

The unobservable preference shifters of the middle and upper tiers of utility, $a_{i,k}, \tilde{a}_{i,s}$ 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).

The coefficients on the regressors in equation (38) 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, σ are often

[20] 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.

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 $k \in \mathcal{K}\setminus k^*$,

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

We set the trade elasticity to $\eta = 4$ (Simonovska and Waugh, 2014), the elasticity of substitution between crops to $\varsigma = 2$ (Sotelo, 2020) 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 procedure in the literature, we provide only a brief summary here, leaving details to the Appendix Section 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).

We recover lower tier preference shifters, $a_{ji,k}$, and international trade costs, $d_{ij,k}$, from the residuals of gravity equations. We then calibrate the middle tier preference shifters, $a_{i,k}$, to match the share of calories each country consume from each good. Lastly, we adjust the upper tier preference shifter, $\tilde{a}_{i,s}$, to match the expenditure share in agricultural goods across countries.

For the cost share of inputs $\gamma^L_{k\tau}$, $\gamma^N_{k\tau}$, and $\gamma^M_{k\tau}$, we proceed as follows. To simplify the calibration, we assume no differences in the cost share of inputs between crops — we later relax this assumption. Based on the FAO-GAEZ assumptions to produce the data, we set the use of agricultural inputs in traditional technology to zero, $\gamma^M_{k1} = 0$. Additionally, we set $\gamma^L_{k\tau} = \gamma^N_{k\tau}$ for any τ. We then calibrate γ^M_{k1} to match the cost share of inputs in the USA. Lastly, we pick $\lambda_{k,k'}$ from USDA.

4.1.3 Step 3: Calibrating GHG Emissions

In the third and final step, we estimate the GHG emissions, $\varphi_{k\tau}$. To reduce the data requirements, we assume that the GHG emissions is a combination of a crop-specific component and

a technology-specific component as follows, $\varphi_{k\tau} = \varphi_k \varphi_\tau$. We calibrate the value of φ_k so that the average global emission per food product relative to the average emission across food products in the model matches that same measure in the data produced by PN18. We then estimate φ_0 and φ_1 based on two moments in the data. First, the total GHG emissions from food production in the data. Second, the ratio of the total emissions from food production in the countries above the median GDP per capita versus the emissions of the countries below the median coming from EDGAR-FOOD data.

4.2 Results

4.2.1 Income Elasticities

We present the estimated values of the income elasticity parameters in figure 5a, along with 95% confidence intervals. Recall that these are not equal to the income elasticities, but they have the same ranking within sector. Note that manufacturing is normalized to zero. Figure 5a presents the implied income elasticity (averaged across all countries), calculated using equation (30). The ranking looks as one would expect: potatoes and rice have some of the lowest values, while cocoa and strawberries are on the highest ends. Meats tend to be towards the middle.

In figure 5c, we plot the structural income elasticity values against the corresponding reduced form in equation (1) from empirical pattern three. We see 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 the reduced form. 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.[21]

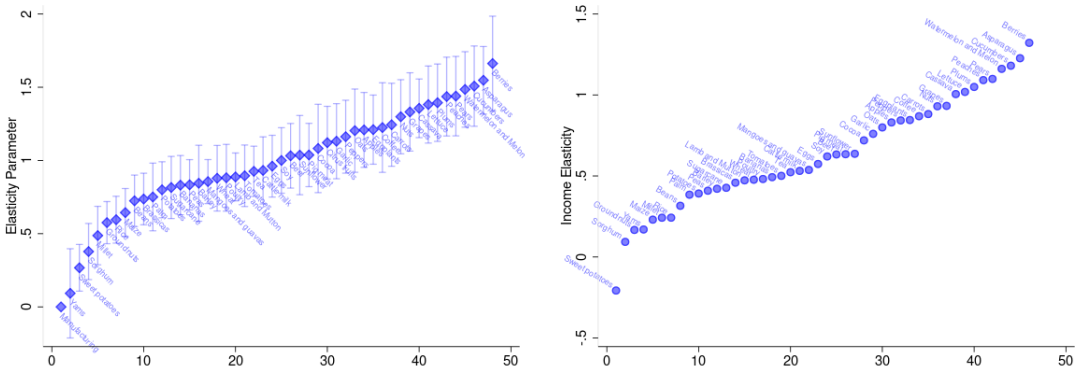
Finally, in Figure 5d, we plot the structural income elasticities against the GHG per calorie of each product, to verify empirical pattern three is replicated by the model. Indeed it is, with a significant positive slope.

[21] 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.

Figure 5: Estimation of Income Elasticities and Parameters

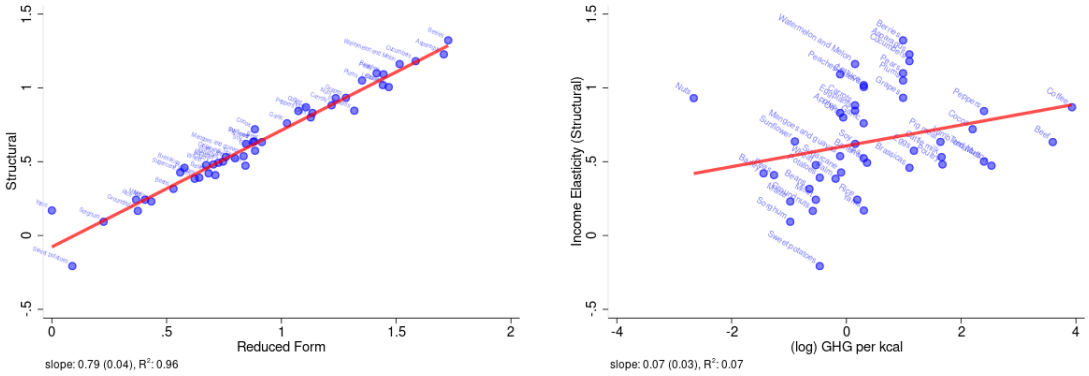
(a) Income Elasticity Parameters, ϵ_k

(b) Structural Income Elasticities, $\mathbb{E}_{i|k}\left[\frac{\partial \ln(p_{i,k}C_{i,k})}{\partial \ln E_i}\right]$



(c) Structural vs Reduced Form Income Elasticities

(d) Structural Income Elast. and GHG emissions/calorie



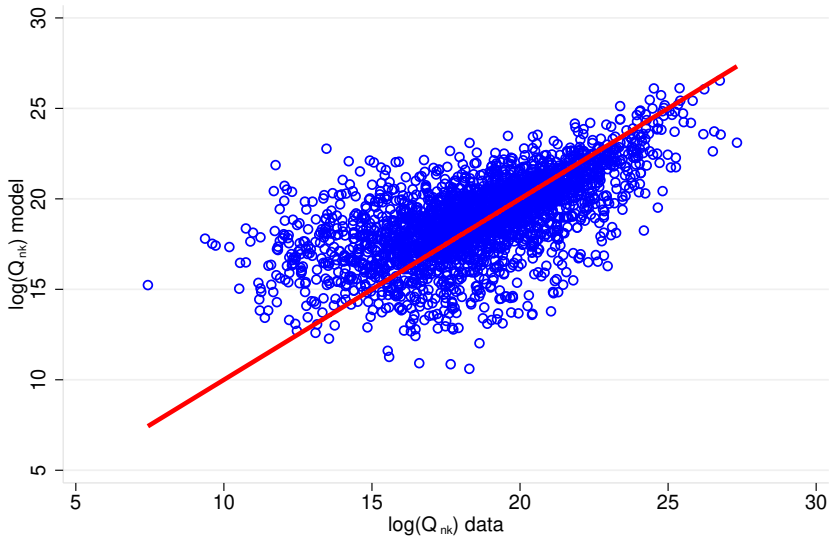
Notes: Panel (a) shows the estimated values (with 95% confidence intervals) of ϵ_k by product. Panel (b) shows the implied income elasticities from equation (30). Panel (c) shows the relationship between the structural values of the income elasticities and the reduced form values — equation (1). Panel (d) shows the relationship between the structural income elasticities and GHG emissions per calorie.

4.2.2 Fit of the Model

This section shows that the model replicates key patterns in the data related to agricultural production, GHG emissions, and economic development. We underscore that none of the empirical patterns that we present here were directly targeted in our quantification procedure.

Agricultural production and Economic Development. Figure 6 shows the fit of the model in terms of aggregate production by country. The model performs well in terms of matching the relative quantities produced across countries for each crop. Figure 7a shows the model generates a decreasing share of workers in agriculture, a well-known empirical regularity

Figure 6: 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 crop. 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.

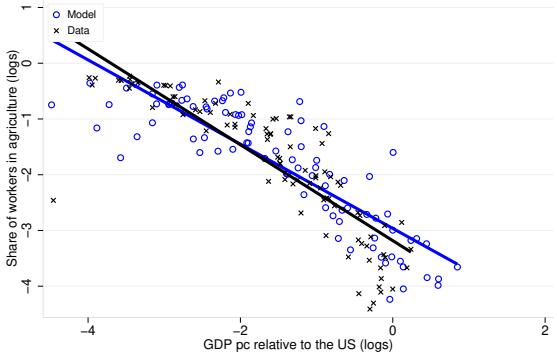
from the literature (Comin et al., 2021; Herrendorf et al., 2014), and Figure 7b shows an increasing cost share of inputs with economic development, as referenced in empirical pattern 4.

CO2 Emission, Calories and Economic Development.

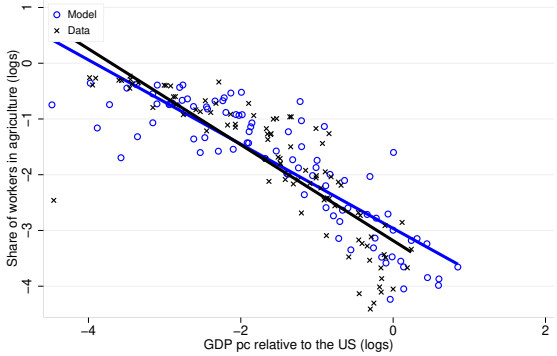
Figure 7 d), e) and f) show that the model replicates the relationships observed in empirical pattern 2: food GHG emissions increase, both in per capita and per calorie terms, and calories increase.

Figure 7: Fit of the Model: relationships with GDP per capita

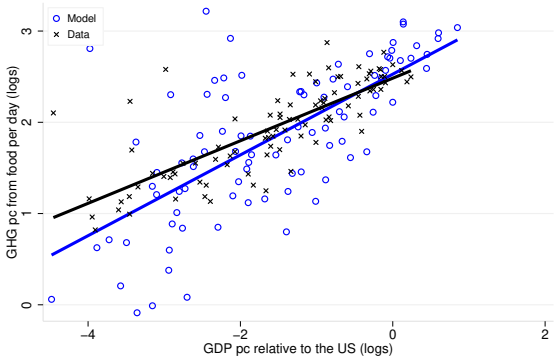
(a) Employment in Agriculture



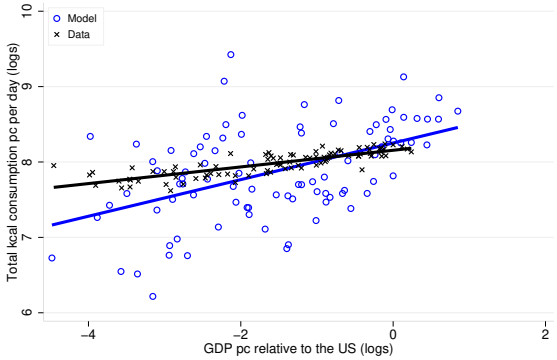
(b) Cost Share of Inputs



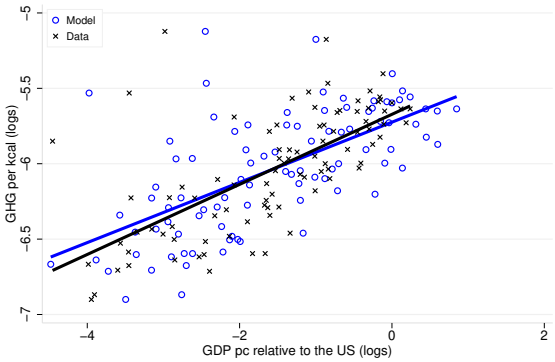
(c) Food GHG per capita



(d) Calories per capita



(e) 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 circles, we have the actual data and, in black line, the best linear fit predicted by the model. In blue, we have the corresponding elements in the data.

5 Quantitative Exercises

5.1 Decomposing the Relationship between Emissions and Income

GHG emissions from food is strongly increasing with income in the data — see empirical pattern 2 (Figure 2a). Identifying the causal drivers of this relationship is key for understanding the implications of economic growth for emissions. We provide insight into this in this section by using the model to decompose this relationship. Specifically, we remove the contribution of confounding factors that are not driven by economic growth.

The results are in table 3. In each column, we show the coefficient from a regression of log GHG emissions per capita on log income per capita. Column (1) shows the relationship under the calibrated model, which closely replicates empirical pattern 2 (Figure 2a). In the remaining columns, we present the coefficient estimate when some features of the model are turned off.

In column (2), we remove the effect of intrinsic diet preferences, such as due to differences in demographics and culture. We do this by setting $a_{i,k}$, which captures these preferences, equal across countries within each agricultural product, specifically equal to the population-weighted average, $\sum_{j \in \mathcal{I}} a_{j,k} \cdot \frac{N_j}{\sum_{j'} N_j}$. The coefficient becomes about two-thirds smaller in size. That is, a large reason why food emissions is increasing with income is because of intrinsic preferences for diet: rich countries tend to consumer emission-intense products not because they are richer, but because of other preferences for diet, that happen to be correlated with income.

In column (3), we remove the effect of comparative advantage in agricultural production. We do this by setting $T^f_{i,k\tau}$ equal across countries within each product and technology, specifically to the population-weighted average. The coefficient is insignificantly different, suggesting that comparative advantage is not driving this relationship.

In column (4), we remove the effect of agricultural trade costs. We do this by setting the domestic trade costs equal across countries within each agricultural, specifically equal to the population-weighted average, and the same for foreign trade costs. The coefficient is insignificantly different, suggesting that geographic position in the world is not driving this relationship.

Finally, in column (5), we remove 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, similar to the case of column (2), which is expected given the other columns give little difference.

Summarizing, removing the confounding variation reveals an 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 Food GHG Emissions and Income

	(1)	(2)	(3)	(4)	(5)
GDP per capita (log)	0.523***	0.151**	0.494***	0.523***	0.185**
	(0.042)	(0.072)	(0.043)	(0.052)	(0.072)
Observations	91	91	91	91	91
Adjusted R^2	0.630	0.094	0.607	0.506	0.136
Counterfactual	Baseline	Demand	Supply	Geography	All

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the regression of log food GHG kg per capita on log GDP per capita. 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 Aggregate Effects of Environmental Policies

We analyze the effect of various counterfactual policies both on global welfare and global GHG emissions from food. We then decompose the effect on emissions to isolate the channels of transmission.

The results are presented in table 4. Each row corresponds to a different counterfactual. Column (1) shows the effect on global welfare, which we measure as population-weighted average utility. Column (2) the effect on global GHG emissions from food, $\sum_{i\in\mathcal{I}} G_i$. Columns (3) to (5) decomposes the effect on emissions using the following

$$\sum_{i\in\mathcal{I}} G_i = \sum_{i\in\mathcal{I}} \sum_{k\in\mathcal{K}_A} \sum_{\tau\in\{0,1\}} \varphi_{k\tau} \cdot \underbrace{\frac{Q^C_{i,k,\tau}}{Q^C_{i,k}}}_{\text{technology}} \cdot \underbrace{\frac{Q^C_{i,k}}{Q^C_i}}_{\text{diet}} \cdot \underbrace{Q^C_i}_{\text{scale}}$$

Column (3), technology, corresponds to only the technology shares within food product, $\frac{Q^C_{i,k,\tau}}{Q^C_{i,k}}$, taking their counterfactual values, while keeping the total calories by product, $\frac{Q^C_{i,k}}{Q^C_i} \cdot Q^C_i$, fixed at the baseline. Column (4), diet, corresponds to only the share of calories by food product, $\frac{Q^C_{i,k}}{Q^C_i}$, taking their counterfactual values. Column (5), scale, corresponds to only the total amount of calories across all food products, Q^C_i, taking their counterfactual values, with the shares between products and technology remaining unchanged.

In the final two columns, we present a decomposition of a different nature. In column (7), we calculate the change in emissions due to the change in the diet shares (total expenditure fixed) coming solely from the change in real income, U_i. This could be understood as a partial

equilibrium effect, as prices are held fixed. In column (8), where relevant, we calculate the back-of-the-envelope, mechanical effect of the counterfactual. That is, the model is not used, we simply replace the production quantities with that imposed in the counterfactual, holding everything else fixed.

Now, turning to the results:

Economic growth. The first two rows show counterfactuals under a change in TFP: in row one, the change in TFP in the non-agricultural sector, and row two, the change in TFP in the agricultural input sector. The effect on welfare, column (1) is greater under the non-agricultural shock, which makes sense given the direct benefit consumers receive from a reduction in prices. The effect on emissions, column (2), is much greater for the TFP shock in agricultural inputs. The decomposition reveals that this in part reflects the increase in the use of modern technology, column (3), which is the environmental implication of agricultural modernization, and an overall increase in agricultural consumption, column (5). Whereas, for the TFP shock in the non-agricultural sector, overall agricultural consumption falls, column (5), reflecting that non-agricultural products are now cheaper. Column (6) reveals that the partial equilibrium effect of both these shocks on emissions is much greater. Understandably, upward sloping agricultural supply attenuates the expansion in agricultural production.

Diet change. Rows three and four show counterfactuals under a change in diet: in row three, we consider a world where no-one consumes beef, in row four, where everyone is vegetarian. We implement this by setting TFPs in these sectors close to zero, essentially mimicking a sufficiently large tax (there will be no tax revenue because production goes to zero). We see welfare, column (1), declines in both cases, which we would expect due to love-for-variety in preferences across food products. Emissions, column (2), in both cases declines, with the decline being greater in the vegetarian case. Again, expected, given meat products typically have greater emissions than non-meat products, and that the vegetarian counterfactual reduces the consumption of more meat products than just no beef.

Trade change. Rows five and six show counterfactuals under a change in trade: in row five, we consider the case where agricultural products are only purchased locally, and in row six, where agricultural inputs are only sourced locally. In both cases, we implement these by sending the relevant trade costs to infinity. Eating locally reduces welfare, while sourcing inputs locally seems to raise welfare.. Eating locally has a much greater reduction in emissions than sourcing inputs locally. The decomposition shows this is mostly due to a reduction in the overall consumption of agricultural products, column (5). That is, forcing consumers to

buy locally causes a reduction in purchasing power, resulting in less consumption of agricultural products overall. For sourcing inputs locally, changes in technology drive most of the effect, column (3), suggesting that producers are able to access agricultural inputs more cheaply on the international market.

Table 4: Aggregate Effects of Alternative Policies

Counterfactual	Welfare	GHG Emissions					
		Total	Technology	Diet	Scale	Income	Mechanical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TFP growth (non-agr.)	9.67	0.42	0.03	0.70	-0.31	9.32	-
TFP growth (inputs)	2.56	3.68	0.84	-0.06	2.85	3.33	-
No beef	-0.12	-27.13	-27.14	-25.81	-2.12	-16.45	-27.11
Vegetarian	-0.96	-46.72	-46.89	-40.78	-10.57	-35.29	-46.80
Eating locally	-0.59	-6.45	-3.21	1.51	-9.68	-2.14	-
Sourcing inputs locally	0.43	-1.37	-2.08	-0.14	0.56	-0.58	-

Notes: This table shows the impact of different counterfactuals on aggregate welfare and CO2 emissions. Each cell is a percentage change relative to the basline. Column (1) is the change in aggregate welfare (utility across countries weighted by population size). Column (2) is the change in global emissions. Columns (3)-(7) present decompositions of the change in global emissions.

6 Conclusion

This paper highlights the link between economic development and greenhouse gas (GHG) emissions from food production. Through our quantitative, multi-country, general equilibrium model, we have demonstrated that both diet composition and agricultural modernization are critical drivers of the increase in GHG emissions as countries become wealthier. Our analysis shows that as economies grow, the nutrition transition towards meat and high-emission food products significantly contributes to higher emissions per capita. Simultaneously, the modernization of agricultural practices, particularly the use of fertilizers and machinery, exacerbates this trend.

We examine policy counterfactuals such as adopting vegetarian diets or reducing trade barriers as potential pathways to mitigate emissions, and enumerate the trade-off in terms of welfare. Our findings suggest that sustainable development policies should carefully consider both the environmental impact of dietary changes and the broader economic consequences of agricultural production strategies.

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

Not for Publication

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OA Data

This section describes in detail the data construction for this paper

Calories Intake. XXX

GHG emissions. XXX

Trade and Production. XXX

OB Complementary Empirical Patterns

This section presents complementary empirical patterns about CO2 emissions and GDP per capita.

OB.1 Complementary Empirical Pattern 1. Across households, agricultural goods with high levels of CO2 emissions have a high income elasticity.

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. Table O.2 shows that, in the household data, our point estimates are smaller. However, the qualitative results hold across specifications, with and without excluding meat products.

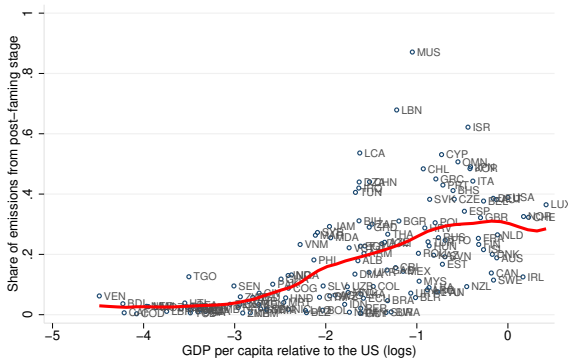
The positive correlation between product income elasticities and product GHG emissions imply that diets consist more of environmentally harmful products as societies get richer. Motivated by this empirical pattern, our model will feature nested non-homothetic CES preferences, which will allow for different income elasticities by food product. In section 3.4, we revisit equation 1 and show how our model's structural parameters related to the reduced form coefficients, α, in equations (1) and (O.1).

OB.2 Complementary Empirical Pattern 2. The share of CO2 emissions from farm production relative to food processing increases with GDP per capita.

The fifth explores the relationship between economic development and the food processing industry. As discussed in **?**, food production tends to shift from within the household to industry. Figure O.1 shows

the environmental implications of that shift in food processing. There is a notable increase in the share of CO2 emissions derived from food processing relative to farm production with GDP per capita. In low-income countries, such as Senegal, Togo and Congo, the share of CO2 emissions from food processing stage is less than 20%. In high-income countries such as Italy, Spain and the USA that share rises to more than 35%.

Figure O.1: Share of GHG emissions from food processing relative to farm production



Notes: Panel (a) uses EDGAR-FOOD data measures of GHG emissions from in-farm production. Panel (b) shows the CO2 emissions from the use of fertilizers and energy in farm production from FAO-STAT.

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

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

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 (27) and (29)

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

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

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

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

Elasticity of overall price index, P_i:

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

$$
\begin{aligned}
\left(1 - \sigma + \frac{1-\sigma}{1-\varsigma} \bar{\epsilon}_i \right) \frac{\partial \ln P_i}{\partial \ln E_i} &= \frac{1-\sigma}{1-\varsigma} \bar{\epsilon}_i \\
\frac{\partial \ln P_i}{\partial \ln E_i} &= \frac{\bar{\epsilon}_i}{1-\varsigma+\bar{\epsilon}_i}
\end{aligned} \tag{O.5}
$$

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 (32)

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

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

Where the first equality used equation (30) and that all products are in the same sector, $s(k) = s(k') = s(k'') = s$; the third equality used equation (27).

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.

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 $\tilde{C}^*_{i,s}$

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

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

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

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 nonhomothetic 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)

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

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 (33):

Proof. Totally differentiating equation (26),

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

where in the first equality we used that $d\ln Q^C_{i,k\tau} = d\ln Q_{i,k\tau}$, 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

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

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

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

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

rewrite this using

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

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

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

which is the decomposition given in equation (33). □

Proving equation (34):

Proof. Taking the derivative,

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

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

$$\sum_{\tau'}\left(I_{\tau,\tau'}-\frac{Q_{i,k\tau'}}{Q_{i,k}}\right)\frac{\partial \ln h^f_{i,k\tau'}}{\partial \ln w_i}=\overbrace{\left(1-\frac{Q_{i,k\tau}}{Q_{i,k}}\right)}^{=\frac{Q_{i,k,1-\tau}}{Q_{i,k}}}\frac{\partial \ln h^f_{i,k\tau}}{\partial \ln w_i}-\frac{Q_{i,k,1-\tau}}{Q_{i,k}}\frac{\partial \ln h^f_{i,k,1-\tau}}{\partial \ln w_i}$$
$$=\frac{Q_{i,k,1-\tau}}{Q_{i,k}}\left(\frac{\partial \ln h^f_{i,k\tau}}{\partial \ln w_i}-\frac{\partial \ln h^f_{i,k,1-\tau}}{\partial \ln w_i}\right)$$
$$=-\frac{Q_{i,k,1-\tau}}{Q_{i,k}}\left(\frac{\gamma^N_{k\tau}}{\gamma^L_{k\tau}}-\frac{\gamma^N_{k,1-\tau}}{\gamma^L_{k,1-\tau}}\right) \tag{O.23}$$

where the third equality used that $\frac{\partial \ln h^f_{i,k\tau}}{\partial \ln w_i}=-\frac{\gamma^N_{k\tau}}{\gamma^L_{k\tau}}$, 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

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

which is the desired expression, equation (34) □

For enumera

OD Quantifying the Model

OD.1 Estimation of the Income Elasticity Parameters

Derivation of equation (37): starting from equation (6)

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

Derivation of equation (38): 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 (36)} \\
&= \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 (35)} \\
&= \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}^F_{\mathcal{I}^{\neg 0}_{i,k^*}, k^*}\right] + \cdots \\
&\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 (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^*)} + \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)
\end{aligned}
$$

OD.2 Algorithm to Calibrate and Solve the Model

TBD

OE Online Appendix Figures and Tables

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

	Specification			
	(1)	(2)	(3)	(4)
a. All products				
$\log(\text{GDPPC})_{i,t} \times \log(\text{CO2PK})_{i,t}$	0.149***	0.111***	0.148***	0.110***
	(0.029)	(0.030)	(0.029)	(0.030)
R2	0.880	0.891	0.880	0.891
Obs	353199	353199	353199	353199
b. Excluding meat products				
$\log(\text{GDPPC})_{i,t} \times \log(\text{CO2PK})_{i,t}$	0.338***	0.197*	0.343***	0.200**
	(0.096)	(0.101)	(0.095)	(0.101)
R2	0.908	0.917	0.909	0.917
Obs	179333	179333	179333	179333
Controls				
- Exporter x Good x Year	Y	Y	Y	Y
- Exporter x Importer x Year	Y	Y	Y	Y
- Exporter x Importer x Good	Y	Y	Y	Y
- Exporter x Importer Region x Good x Year	-	Y	-	Y
- Proxy for Price Index	-	-	Y	Y

Table O.2: Income Elasticity and GHG Emissions per calorie

	Specification		
	(1)	(2)	(3)
a. All products			
$\log(\text{HHINCOME})_i \times \log(\text{CO2PK})_k$	0.043***	0.023***	0.017***
	(0.001)	(0.002)	(0.003)
R2	0.496	0.661	0.804
Obs	232696	232696	232696
b. Excluding meat products			
$\log(\text{HHINCOME})_i \times \log(\text{CO2PK})_k$	0.023***	0.028***	0.015***
	(0.001)	(0.002)	(0.003)
R2	0.484	0.614	0.787
Obs	181104	181104	181104
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.3: Crosswalk - Poore and Nemecek vs. FAO

Good	Poore and Nemecek (2018)	FAOSTAT
Apples	Apples	Apples
Bananas	Bananas	Bananas
Barley	Barley	Barley
Beef (beef herd)	Beef (beef herd)	Meat of buffalo, fresh or chilled; Meat of cattle with the bone, fresh or chilled; Meat of cattle boneless, fresh or chilled; Bovine meat, salted, dried or smoked
Beet Sugar	Beet Sugar	Sugar beet
Blueberries	Berries and Grapes	Blueberries
Brassicas	Brassicas	Cauliflowers and broccoli
Cane Sugar	Cane Sugar	Sugar cane; Cane sugar, non-centrifugal
Cassava	Cassava	Cassava, fresh; Cassava, dry
Cheese	Cheese	Cheese from milk of sheep, fresh or processed; Cheese from skimmed cow milk; Whey cheese; Cheese from milk of goats, fresh or processed; Cheese from whole cow milk; Processed cheese
Cherries	Berries and Grapes	Cherries
Citrus Fruit	Citrus Fruit	Oranges; Other citrus fruit, n.e.c.; Kiwi fruit; Tangerines, mandarins, clementines; Lemons and limes
Coffee	Coffee	Coffee, green
Cranberries	Berries and Grapes	Cranberries
Dark Chocolate	Dark Chocolate	Cocoa beans; Chocolate products nes
Eggs	Eggs	Hen eggs in shell, fresh; Eggs, liquid; Eggs, dried; Eggs from other birds in shell, fresh, n.e.c.
Gooseberries	Berries and Grapes	Gooseberries
Grapes	Berries and Grapes	Grapes
Groundnuts	Groundnuts	Groundnuts, shelled; Groundnuts, excluding shelled
Lamb and Mutton	Lamb and Mutton	Meat of goat, fresh or chilled; Meat of sheep, fresh or chilled
Maize	Maize	Maize (corn)

Table O.4: Crosswalk - Poore and Nemecek vs. FAO (continued)

Good	Poore and Nemecek (2018)	FAOSTAT
Milk	Milk	Raw milk of sheep; Raw milk of cattle
Nuts	Nuts	Brazil nuts, in shell; Areca nuts; Kola nuts; Walnuts, in shell; Hazelnuts, shelled; Chestnuts, in shell; Pistachios, in shell; Other nuts (excluding wild edible nuts and groundnuts), in shell, n.e.c.; Hazelnuts, in shell; Cashew nuts, shelled; Walnuts, shelled; Karite nuts (sheanuts); Cashew nuts, in shell; Almonds, in shell; Brazil nuts, shelled; Almonds, shelled
Oatmeal	Oatmeal	Oats, rolled; Oats
Olive Oil	Olive Oil	Olive oil; Oil of olive residues
Onions and Leeks	Onions and Leeks	Leeks and other alliaceous vegetables; Onions and shallots, dry (excluding dehydrated); Onions and shallots, green
Other Pulses	Other Pulses	Broad beans and horse beans, dry; Chick peas, dry; Vetches; Beans, dry; Lentils, dry; Cow peas, dry; Other beans, green; Other pulses n.e.c.; Bambara beans, dry
Other berries and fruits of the genus vaccinium n.e.c.	Berries and Grapes	Other berries and fruits of the genus vaccinium n.e.c.
Palm Oil	Palm Oil	Palm oil; Oil of palm kernel
Peas	Peas	Peas, green; Peas, dry
Pig Meat	Pig Meat	Meat of pig with the bone, fresh or chilled; Meat of pig boneless, fresh or chilled
Pomelos and grapefruits	Berries and Grapes	Pomelos and grapefruits
Potatoes	Potatoes	Potato offals; Potatoes, frozen; Potatoes; Sweet potatoes
Poultry Meat	Poultry Meat	Meat of geese, fresh or chilled; Meat of turkeys, fresh or chilled; Meat of pigeons and other birds n.e.c., fresh, chilled or frozen; Meat of ducks, fresh or chilled; Meat of chickens, fresh or chilled
Rapeseed Oil	Rapeseed Oil	Rapeseed or canola oil, crude
Raspberries	Berries and Grapes	Raspberries
Rice	Rice	Rice; Rice, broken
Root Vegetables	Root Vegetables	Carrots and turnips; Chicory roots
Rye	Wheat and Rye	Rye
Strawberries	Berries and Grapes	Strawberries
Sunflower Oil	Sunflower Oil	Sunflower-seed oil, crude
Tofu (soybeans)	Tofu (soybeans)	Soya curd
Tomatoes	Tomatoes	Tomatoes, peeled (o/t vinegar); Tomatoes
Wheat	Wheat and Rye	Wheat

Figure O.2: GHG emissions per kilocalorie across food products

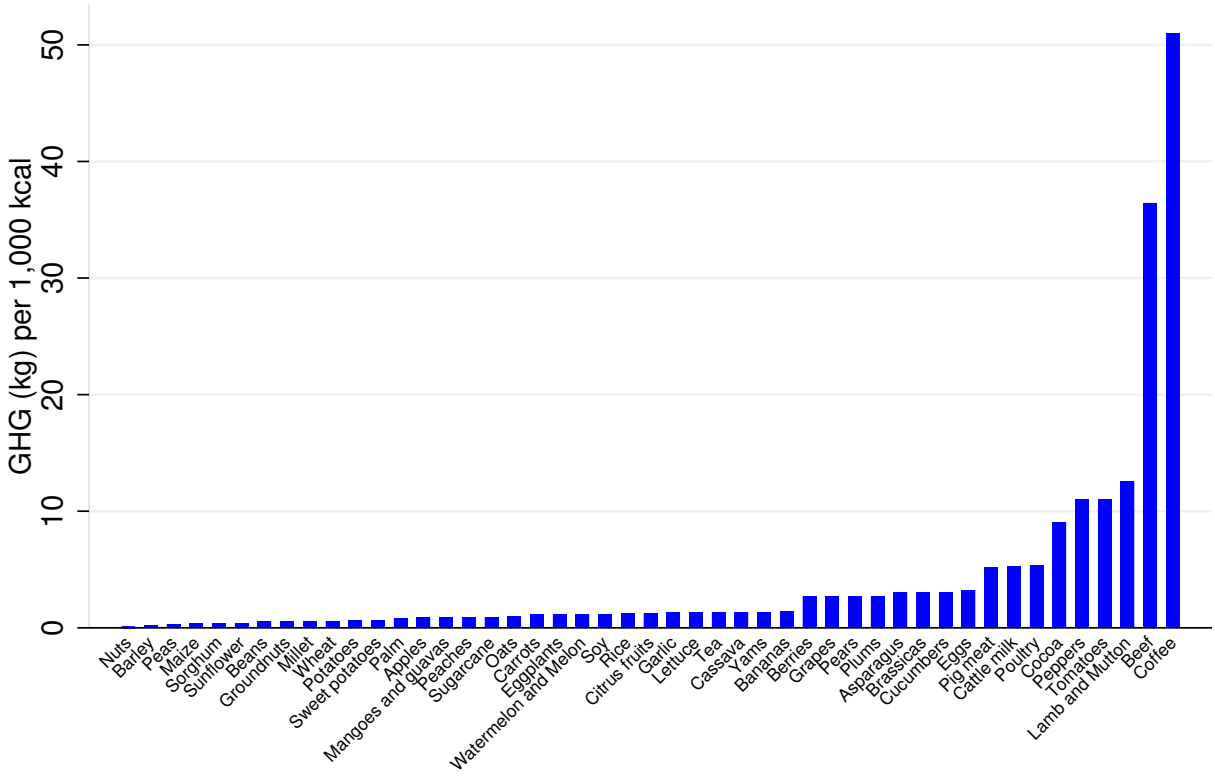
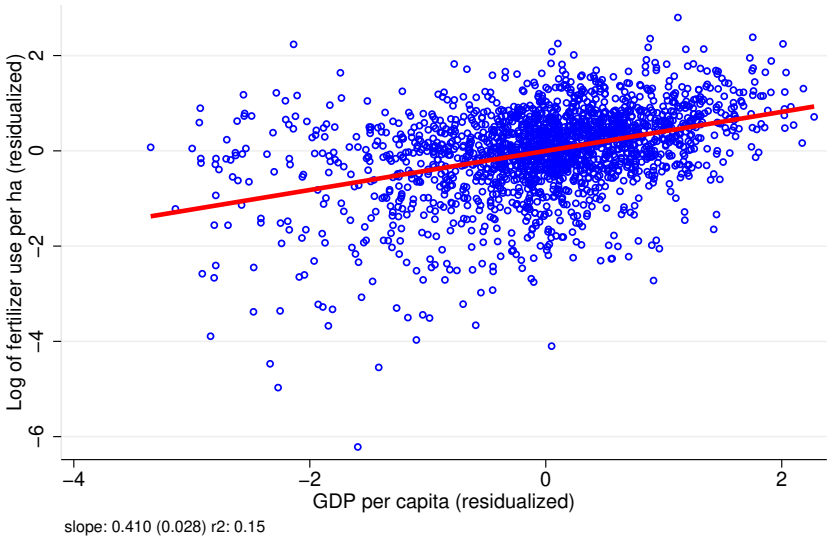


Figure O.3: GHG emissions per kilocalorie across food products within country



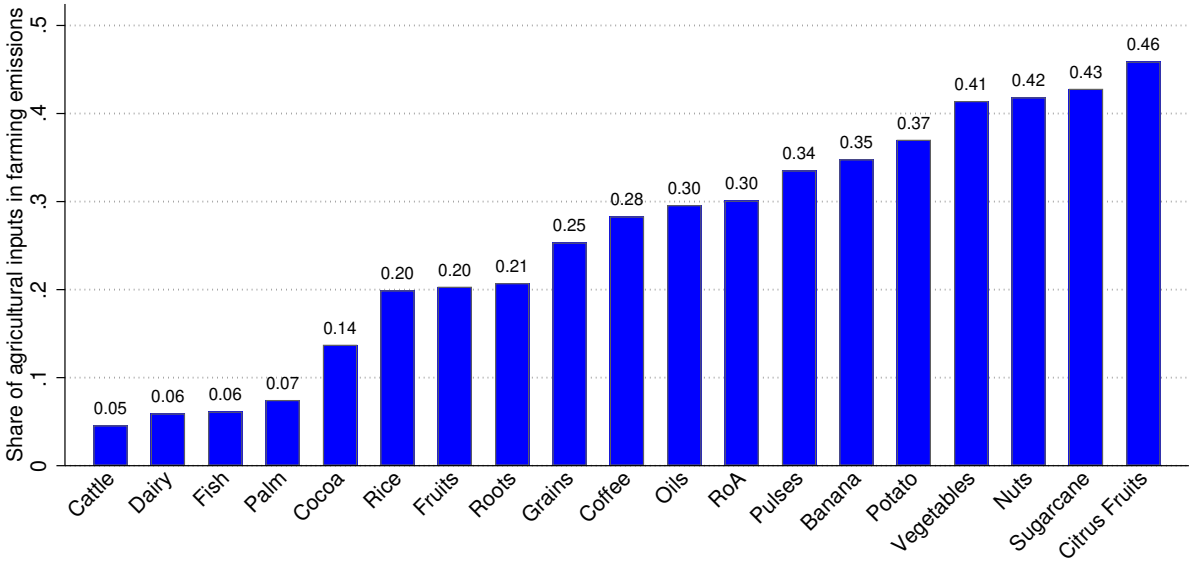
Notes: To construct this figure we use panel data information on CO2 emissions over time across countries. We employ data from 2010 to 2020. We residualize from the y-axis and the x-axis country fixed effects, so that only within country variation remains in the figure.

Figure O.5: 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.

Figure O.4: Share of GHG Emissions from agricultural inputs (PN18)



Appendix References