Trade, Technology, and Agricultural Productivity

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Abstract

We examine the contribution of trade to the rise of modern agriculture, taking into account interactions between trade, input requirements, and technology adoption. We develop and estimate a new multi-country general equilibrium model that incorporates producers' choices of which crops to produce and with which technologies, at the level of grid-cells covering the Earth's surface. We find that trade cost reductions in agricultural inputs and the international transmission of productivity growth in the agricultural input sector since the 1980s induced large shifts from traditional, labor-intensive technologies to modern, input-intensive ones, with important global and distributional implications for productivity and welfare.

Keywords: Trade, Technology, Intermediate Inputs, Productivity, Agriculture

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1 Introduction

Production technologies that have enhanced the conditions of human life around the world often require the use of certain intermediate inputs, ranging from semiconductors for electronics, garment machinery for textiles, or tractors for agriculture. In many countries and industries, producers largely depend on international trade to procure these inputs. The interaction between technology choices, input requirements, and international trade is, therefore, important for examining the welfare implications of technology adoption across the world.

One sector in which technology adoption has had a dramatic effect on economic welfare is agriculture. Agricultural modernization, reflected by a shift from traditional, labor-intensive technologies to modern, input-intensive ones, has long been argued to be a central feature of economic development (Johnston and Mellor, 1961; Schultz et al., 1968; Gollin, Parente, and Rogerson, 2007). The role of international trade for such a shift, however, has not yet been explored. This paper provides the first study of the effects of trade on the rise of modern agriculture and the implications for welfare and agricultural productivity around the world.

Methodologically, agriculture gives us a rare opportunity of observing direct measures of factor productivities—measures that are otherwise inferred from residuals of production functions. The mapping between conditions of land and climate to crop output is scientifically well-measured, and that mapping is known under which technology, whether traditional or modern, is adopted. We bring in measures of land productivity from the Food and Agriculture Organization's Global Agro-Ecological Zones (FAO-GAEZ) for every crop-technology pair at more than a million grid cells (fields) around the world. We exploit these extremely rich data in a new quantifiable, general-equilibrium model that incorporates micro-level choices of which crops to grow and with which technology to grow them.

We tune our general equilibrium analysis to address two broad questions. First, what were the consequences of the fall of trade barriers in the recent decades, often referred to as "globalization", on technology adoption, agricultural productivity, and welfare around the world? We are particularly interested in comparing the relative importance of globalization in agricultural inputs (via technology adoption) to globalization in agricultural outputs (via international crop specialization). Second, how was productivity growth in the production of agricultural inputs, such as farm machinery, fertilizers, and pesticides, transmitted across borders by means of trade? Of our particular interest is the relative importance of the productivity growth coming from foreign sources of inputs compared to domestic ones. In answering these questions, we also seek to understand the distributional implications of trade across countries with different levels of development.

In our framework, we consider a world that consists of multiple countries, each encompassing numerous fields. In every field, crops can be produced by different technologies that are characterized by their intensities of land, labor, and agricultural inputs. Choices of crops and technologies depend on both market and agro-ecological conditions. As for market conditions, higher relative prices of a crop encourage the allocation of resources to the production of that crop, and higher wages or lower prices of inputs incentivize the use of labor-saving, input-intensive technologies. As for agro-ecological conditions, we adopt a parsimonious, yet flexible specification that allows us to exploit the field-level measures of land productivity from FAO-GAEZ. Specifically, we let land productivities be heterogeneous within every field based on a generalized Fréchet distribution, which gives rise to tractable field-level production possibility frontiers (PPFs). These PPFs are fully characterized by two parameters that discipline the marginal rates of substitution between crops and between technologies within crops (i.e., the curvature of the PPF), and agro-ecological parameters that shift the scale of production in a field for every crop-technology pair (i.e., the scale of the PPF).

By incorporating choices of both crops and technologies, we introduce a new source of gains from trade. It is well-studied that trade in crops (i.e. agricultural outputs) generates efficiency gains by making room for international crop specialization. In our framework, trade in agricultural inputs also generates efficiency gains by providing access to inputs that are required for the use of modern, input-intensive technologies. We trace the marks of this new mechanism on the welfare gains from trade. Using a pared down version of our model, we show that, relative to the well-known result of Arkolakis, Costinot, and Rodriguez-Clare (2012), a novel term appears in the gains from trade formula that depends on the share of land under traditional technology and a parameter that governs the marginal rate of substitution between traditional and modern technologies (i.e., the curvature of the PPF along the technology dimension).

We bring our model to a host of data at the level of countries and fields. Our baseline data cover 65 countries and a rest-of-the-world region in year 2007, with information on trade, production, and agricultural input use—including farm machinery, fertilizers, and pesticides. To estimate demand side parameters, we follow standard practices. To estimate model-implied PPFs, we search for the values of the two parameters controlling the curvature of PPFs by minimizing the distance between moments in the data and their model counterparts, while using the FAO-GAEZ data to calibrate field-level shifters. Specifically, one set of our moments is based on spatial variations in the land use of crops: Countries with relatively larger agro-ecological productivity in a crop tend to produce that crop more intensively if PPFs feature less curvature in substitution between crops. Another set of our moments is based on cross-country measures of agricultural input-intensity: Countries with higher wages and lower input prices tend to adopt modern technologies more intensively if PPFs feature less curvature in substitution between technologies.

Our estimated model fits several key cuts of data very well. It closely fits the data on output quantities, prices, and land use of crops across countries. It also predicts very well the relationship between countries' level of economic development and several key measures of agricultural input-intensity.

Based on spatial variations in market and agro-ecological conditions, our model implies large cross-country differences in technology choices: the share of land under modern agricultural technology is 35% in the first quartile of the GDP per capita and 95% in the fourth quartile. Before turning to our counterfactual exercises, we utilize our estimated model to carry out a decomposition exercise that sheds light on the sources of agricultural technology differences across the world. Our decomposition exercise shows that variations in prices and wages (market conditions) account for two-thirds of model-implied differences in technology choice, and that variations in agro-ecological propensity (natural conditions) account for the remaining one-third. Zooming into the market conditions, the contribution of agricultural input prices are as important as wages, and cross-country differences in access to foreign inputs account for about one-third of variations in input prices.

We then perform counterfactual exercises to provide quantitative answers to our two broad questions. We start by examining how reductions in trade costs in the recent decades shaped agricultural productivity and welfare across the world. To do so, we simulate a counterfactual in which trade costs in agricultural outputs and inputs are set back to their estimated level in 1980, and compare the resulting equilibrium with that in the baseline of 2007. We find notable productivity gains, reflected by 4.0% increase in food consumption and 2.5% rise in welfare at the global scale.

To separate the effects of input-side mechanisms (by way of technology adoption) from output-side mechanisms (by way of international crop specialization), we run two additional counterfactuals in which we examine, separately, globalization in only agricultural inputs and only agricultural outputs. Comparing their implications for agricultural productivity, food consumption, and welfare at the global scale, we find that mechanisms on the input side are quantitatively as important as those on the output side. These results tell us that we would miss much in evaluating productivity and welfare effects of globalization if we were to ignore input-side mechanisms.

In addition, we find that the distributional implications of these two mechanisms are substantially different. Globalization in agricultural outputs particularly benefits low-income countries because they have a larger expenditure share on food. This leads to lower welfare inequality between low- and high-income countries. In contrast, due to two distinct channels, globalization in agricultural inputs benefits middle-income countries the most. First, it increases the adoption of modern technologies; second, it increases productivity in the land already using modern technology. While the first channel is virtually muted in high-income countries (since they already have a large share of land under modern technologies), the second channel is negligible in low-income countries (since they have a small share of land under modern technologies). As such, globalization in agricultural inputs widens the gap between low- and middle-income countries, while compressing the gap between middle- and high-income countries.

Lastly, we turn to examining our second research question, in which we study how trade transmits the benefits of productivity growth in the production of agricultural inputs across national borders. To this end, we first simulate a counterfactual in which we set productivities in the agricultural input sector for all countries to their estimates in 1980, as well as 66 counterfactuals in which we change these productivities country by country, one at a time. We next compare, for each country, the counterfactual outcomes from input productivity growth in only that country versus productivity growth in all countries. We take the difference between welfare gains in these two counterfactual scenarios as the contribution of the foreign productivity shocks that are transmitted by way of trade in agricultural inputs. We find this contribution to be around 40% for an average country, which indicates that international trade played a major role in sharing the benefits of productivity growth in the agricultural input sector across national borders in recent decades.

These benefits, however, were substantially lower for low-income countries. International productivity growth in the agricultural input sector brings about lower prices of internationally-supplied agricultural inputs. These lower prices particularly benefit agricultural productivities in middle- and high-income countries that have a more widespread use of modern technologies. Consequently, low-income countries lose their competitiveness in exports of agricultural products, which explains their smaller gains from lower prices of agricultural inputs in international markets.

Related Literature. This paper fits into different areas of economics literature. First, it relates to research on the welfare implications of international trade, highlighting the role of multinational production (Ramondo and Rodríguez-Clare, 2013), firm heterogeneity (Eaton, Kortum, and Kramarz, 2011), and input-output linkages (Caliendo and Parro, 2015)— among other mechanisms (for a review, see Costinot and Rodríguez-Clare (2014)). In addition, this paper speaks to studies that evaluate different channels through which trade in inputs increases productivity, including variety gains (Goldberg, Khandelwal, Pavcnik, and Topalova, 2010), quality upgrading (Fieler, Eslava, and Xu, 2018), and global sourcing (Antras, Fort, and Tintelnot, 2017; Farrokhi, 2020).[1] We contribute to these strands of trade literature by embedding into a multi-country general equilibrium setting the interactions between technology choice and input trade. In addition, we focus our analysis on agriculture, which gives us a unique opportunity of

[1]Our paper also speaks to another set of papers on the interaction between trade liberalization and firm-level choices of technologies. This literature examines firms' exports along the distribution of firm size, where a more advanced technology is characterized by larger fixed costs with smaller marginal costs, e.g. see Yeaple (2005) and Bustos (2011). In contrast, we focus on technology differences based on input-intensity, and of our particular interest is how imports of intermediate inputs can affect technology choices.

observing detailed measures of productivities, under the traditional or modern technologies, at a spatially high resolution. Making use of these detailed productivity measures to address key questions in economic development, we broaden our understanding of the welfare implications of international trade.

Our framework builds on general equilibrium models of agricultural trade and specialization, notably Costinot, Donaldson, and Smith (2016) and Sotelo (2020).[2] We expand these existing frameworks by incorporating the choice of with which technology to produce a crop. This is an important contribution for three reasons. First, conceptually, long-run changes to trade barriers, climate conditions, or environmental regulations likely affect not only which crops farmers grow in a region but also with which methods they produce them. Second, by developing a framework that allows for multiple technology choices, we provide a method that can fully exploit the richness of the data from FAO-GAEZ.[3] Third, our formulation, based on a generalized Fréchet distribution, presents a parsimonious way of incorporating flexible choices of both crops and technologies, bringing new mechanisms through which trade shapes productivity.[4]

We also speak to a long-standing literature that studies the role of agriculture in the process of economic development (Schultz et al., 1968; Caselli, 2005; Gollin, Parente, and Rogerson, 2007; Restuccia, Yang, and Zhu, 2008a). We are inspired by insightful discussions about the importance of agricultural inputs and the role of trade for access to them, dating back at least to Griliches (1958) and Johnston and Mellor (1961).[5] Within this literature, several scholars

[2] A few recent papers have used the land-use models developed in these two papers. Gouel and Laborde (2018) revisit the results from Costinot, Donaldson, and Smith (2016) on the relationships between climate change and agricultural production/trade. Bergquist, Faber, Fally, Hoelzlein, Miguel, and Rodriguez-Clare (2019) analyze general equilibrium effects of policy interventions in Uganda. An older literature uses Constant Elasticity of Transformation (CET) functions to discipline land use of crops. See Taheripour, Zhao, Horridge, Farrokhi, and Tyner (2020) for a review of computable general equilibrium models of land use.

[3] While we are the first to construct a general equilibrium model that incorporates productivity measures from FAO-GAEZ for different technologies, a few recent papers have exploited the productivity differences between traditional and modern technologies in these data to construct instrumental variables for changes in agricultural technology over time, e.g. see Bustos, Caprettini, and Ponticelli (2016) and Allen and Donaldson (2020).

[4] Two recent papers have employed generalized Fréchet distributions in applications to Ricardian models of international trade. Lind and Ramondo (2018) make use of similar tools to examine the role of correlations in productivities between countries. Also Lashkaripour and Lugovskyy (2018) show similarities between the nested Fréchet formulation and the nested CES structure. Under nested CES demand, the elasticity of substitution between product varieties within a country are allowed to be larger than those across countries. The resulting gravity-type equation can be derived from a nested Fréchet structure where productivity draws within a country are more similar to those across countries. Here, instead of using such tools to model trade between countries, we rather apply them to study the allocation of land to crops and technologies within a location. We provide a complete set of new derivations for this structure, that are applicable to a wide range of parametric Roy-type models. For example, in a model where workers select in which location and which occupation within a location to work, our tools could be readily used to allow different supply elasticities along the dimension of location and occupation.

[5] Several papers have studied how trade and structural transformation interact in an open economy, albeit not incorporating the role of agricultural modernization, as we do in this paper. For example, Matsuyama (1992) presents a theory to analyze the interplay between comparative advantage in agriculture and long-term growth, Tombe (2015) formulates a global trade model to study drivers of the low levels of agricultural trade

have emphasized the importance of increases in agricultural productivity for the reallocation of labor from agriculture to non-agriculture sectors, a mechanism often referred to as the "push force" (Nurkse, 1953; Rostow and Rostow, 1990).[6] In our framework, productivity growth in the production of agricultural inputs acts as a push force that incentivizes higher adoption of modern, input-intensive and labor-saving technologies. We contribute to this literature by putting this mechanism into global perspective. We show that, by sharing the benefits of foreign productivity growth in agricultural inputs, international trade had a remarkable impact on the adoption of modern agricultural technologies in recent decades.

Lastly, by formulating a new framework for the analysis of agricultural trade, we add to growing research at the intersection of trade and development with applications to agriculture. This literature has evaluated, for example, how agricultural trade shapes welfare (Tombe, 2015), structural transformation (Fajgelbaum and Redding, 2019), and the regional impact of agricultural productivity shocks (Pellegrina, 2020).[7] On a related branch, a rich literature in agricultural economics has examined governments' policies to promote agricultural productivity, see Lee and Helmberger (1985) for an earlier partial equilibrium approach and Hertel (2002) for a review of relevant computational general equilibrium models. In addition to our methodological contribution to this literature, we offer a comprehensive evaluation of the effects of globalization on agricultural productivity.

2 Data and Empirical Patterns

Our baseline data set is organized at two levels of geographic disaggregation, namely, countries and fields (which is interchangeably used across the literature as grid cells or agro-ecological zones). At the country level, it consists of 65 countries and one representative country for the rest of the world. At the field level, it covers approximately 1.1 million fields around the globe. In this section, we briefly describe our data sources, and present three key empirical patterns about trade, input use and technology that guide our modeling choices.[8]

and implications for welfare, and Teignier (2018) studies the contribution of trade to structural transformation in Great Britain and South Korea. For a recent quantitative application of Matsuyama (1992), see Johnson and Fiszbein (2020).

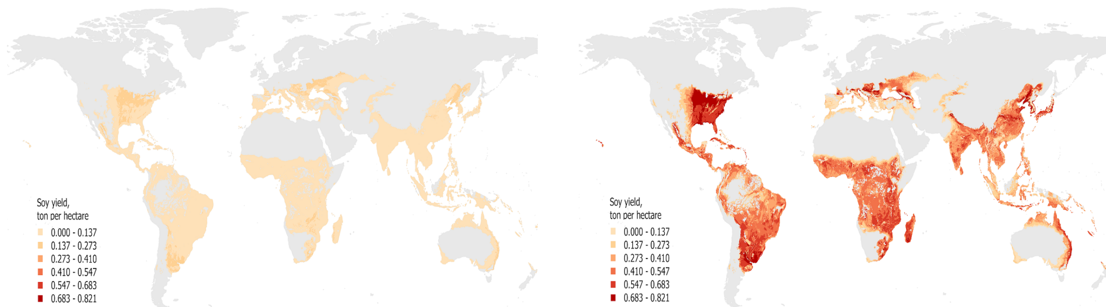
[6]The literature has identified both push forces, coming from productivity gains in agriculture, and pull forces, coming from productivity gains in non-agriculture, as potential sources of reallocation of workers out of agriculture. Using historical data for a selection of countries, Alvarez-Cuadrado and Poschke (2011) find that push forces were the dominant mechanism driving reallocations of labor out of agriculture after the 1960s.

[7]We know of few papers that have examined the impact of trade in fertilizers on agricultural production. Focusing on Africa, Porteous (2020) analyzes the impact of trade in fertilizers and the implications for technology choice. Using reduced-form techniques, McArthur and McCord (2017) evaluate the impact of trade in fertilizers on yields and labor employment in agriculture across countries.

[8]Appendix A provides a detailed description of the construction of our data set.

Figure 1: Potential Yield of Soybean: Traditional (low-input) vs Modern (high-input)

(a) Traditional (b) Modern



Notes: This figure shows the spatial distribution of potential yields of soybean based on FAO-GAEZ data under traditional (labor-intensive) and modern (input-intensive) technology.

2.1 Data

Country-level Data. For two broadly-defined sectors, agriculture and nonagriculture, we collect country-level data on employment, value added, total sales, trade, and consumption. In agriculture, our data cover ten crops (banana, cotton, corn, palm oil, potato, rice, soybean, sugarcane, tomato, and wheat) and three agricultural inputs (fertilizers, pesticides, and farm machinery). For each crop, we gather information on output quantity, land use, prices, and trade. For each agricultural input, we combine bilateral trade with production in values. All these variables in our baseline data are for 2007.

Throughout the paper, we construct several variables that capture the input-intensity of agriculture across countries. In particular, we measure cost share of inputs in agriculture (i.e. expenditure on inputs divided by gross output in agriculture), labor-per-land, and fertilizer-per-land measured as tonnes of fertilizer use divided by total cropland. In addition to our baseline data in 2007, we assemble trade and gross output data for 1980 which we use later to measure changes in trade costs and productivity between 1980 and 2007.

Field-level data. A field corresponds to an agro-ecological zone (AEZ) as a 5 min by 5 min latitude/longitude grid cell encompassing an area of approximately 10 by 10 km. For each field, we collect information from the Food and Agriculture Organization's Global Agro-Ecological Zones (FAO-GAEZ) project, which reports attainable output per unit of land, in tonnes per hectare, if the entire field were allocated to a crop and a given technology were used. These measures of agricultural suitability, reported by crops and types of technology, are referred to as "potential yields". These measures are generated by agronomic models that exploit field-level information on agro-ecological characteristics, such as soil types, elevation, rainfall and temperature, under the assumption that the same economic conditions hold in all fields around the world.

We bring in, for each crop, data on potential yields for two technology types. First, a low-input technology that corresponds to traditional farming activities where production is labor-intensive and there is no use of agricultural inputs. Second, a high-input technology that corresponds to modern systems where production is intensive in the use of agricultural machinery and applications of nutrients and chemical pest, disease and weed control. Hereafter, we call low- and high-input technologies, respectively, "traditional" and "modern".[9] Figure 1 plots potential yields of soybean based on traditional and modern technologies across the world geography.

Lastly, we use data on the total share of cropland in every field around the world from Earthstat. These data are generated by land-classification models that take satellite imagery as inputs.[10]

2.2 Empirical Patterns

Pattern 1. Across countries, cost share of agricultural inputs and input-per-land or per-labor rise with GDP per capita, whereas labor-per-land falls with GDP per capita. A key feature of economic development is that input use in agriculture rises markedly with GDP per capita (e.g. See Restuccia, Yang, and Zhu (2008b), Gollin, Parente, and Rogerson (2007) and Donovan (2017)). Figure 2 revisits these patterns in our data. Panel (a) shows that the cost share of agricultural inputs rises with GDP per capita: It is approximately 25 and 60 percent respectively in the first and fourth quartile of GDP per capita. Panels (b)-(c)-(d) show the scatter plot of labor-per-land, fertilizer-per-land, and fertilizer-per-labor in agriculture against GDP per capita. Countries with higher GDP per capita use fertilizers more intensively relative to land or labor, whereas they save on labor per unit of land.

Given these striking cuts of data, we develop a model that is designed to generate technological differences in agricultural production across countries as an *endogenous* outcome. For instance, in a country where wages are low, or input prices are high, agricultural producers will have incentives to choose traditional, labor-intensive technologies rather than modern, input-intensive ones.

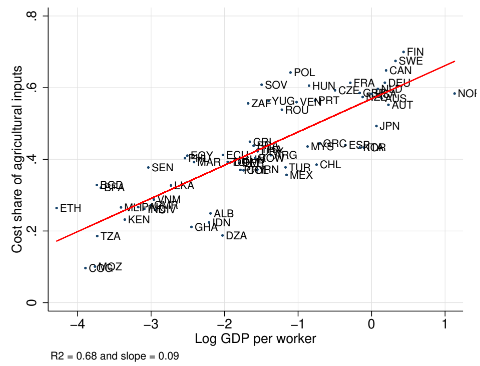
Pattern 2. Across countries, the import share of agricultural inputs is typically large, and exports of agricultural inputs are concentrated in a relatively small num-

[9] According to FAO-GAEZ, the low-input technology represents a production technology with "no application of nutrients, no use of chemicals for pest and disease control" and the high-input production technology is "fully mechanized with low labor intensity and uses optimum applications of nutrients and chemical pest, disease and weed control." In addition, FAO-GAEZ reports potential yields based on an intermediate input intensity, which we do not use in this paper.

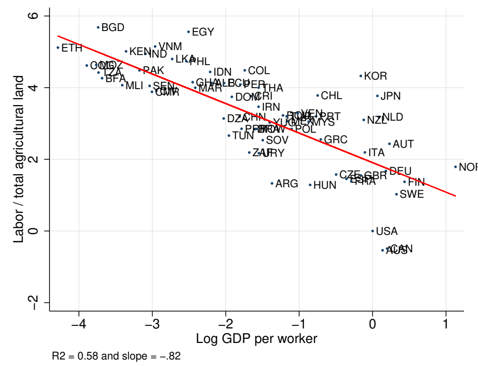
[10] The EarthStat project is a collaboration between the Global Landscapes Initiative at the University of Minnesota's Institute on the Environment and the Land Use and Global Environment Lab at the University of British Columbia.

Figure 2: Cross-Country relationships between Cost Share of Inputs in Agriculture, Input Use and GDP per capita (2007)

(a) Cost share of Agricultural Inputs

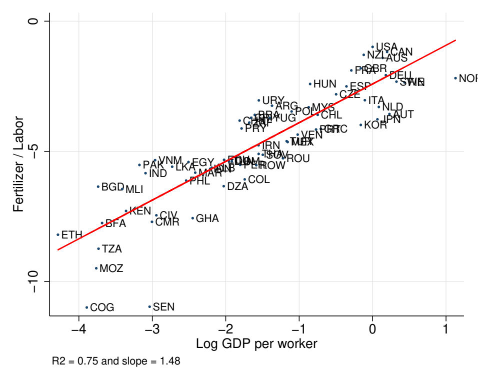


(b) Labor per Land



(c) Fertilizer per Land

(d) Fertilizer per Labor



Notes: This figure plots measures of agricultural input and labor intensity against GDP per capita of countries. Panel (a) shows input cost share, as measured by expenditure on inputs relative to gross output in agriculture. Panel (b) to (d) show fertilizer-per-land, labor-per-land, and fertilizer-per-labor where "fertilizer" is aggregate tonnes of fertilizer use, "land" is the cropland, and "labor" is the labor employment in agriculture.

ber of countries. Given the strong relationship between agricultural input-intensity and economic development that we presented in Pattern 1, we now ask how much countries rely on international trade to procure agricultural inputs. Table 1 shows that the import share of all agricultural inputs combined is typically large, with an average of 0.65 across countries in 2007. It also indicates substantial cross-country heterogeneity in import shares for different inputs: for example, the import share of fertilizers range between 0.36 at the 10th percentile and 0.97 at the 90th percentile. Most countries, in fact, largely depend on international trade to procure at least one of fertilizers, pesticides, or farm machinery. This reflects the high geographic concentration in the production of agricultural inputs. The ten largest exporting countries account for approximately 80% of all the international exports of agricultural inputs. As shown in Table A.1 in the Online Appendix, fertilizer production is concentrated in several countries that have the required natural resources, and the production of pesticides and farm machinery

Table 1: Import Share of Agricultural Inputs

	Imports as share of a country's expenditure				Exports as share of global exports	
	Avg	p10	p50	p90	Top 10	Not top 10
	(1)	(2)	(3)	(4)	(5)	(6)
All	0.65	0.31	0.70	0.91	0.77	0.23
Fertilizer	0.69	0.36	0.74	0.97	0.82	0.18
Machinery	0.67	0.28	0.73	0.93	0.78	0.22
Pesticide	0.69	0.30	0.72	1.00	0.85	0.15

Notes: This table shows the average, and the 10th, 50th, 90th percentiles of import share of agricultural inputs, for the aggregate of agricultural inputs, and by individual input category, in year 2007. In addition, it shows the share of exports of the ten largest exporting countries in the global exports of agricultural inputs.

requires chemical- and machinery-related technologies that might be unavailable to low-income countries.[11]

Motivated by the important role of trade in the use of agricultural inputs (documented in Table 1), in our framework we let countries purchase agricultural inputs domestically and also from international suppliers. This will allow us to examine the importance of trade in intermediate inputs for the adoption of input-intensive agricultural technologies.

Pattern 3. Potential yields of modern technologies over traditional ones are large, vary substantially across fields, and do not vary systematically across countries with different GDP per capita. Figure 4 (a) shows the global average of the modern potential yield premium, as the ratio of potential yield of modern to that of traditional technology, for each crop across fields around the world. These premia are, on average, in the range of four to seven across crops. Figure 4 (b) shows, for the case of soybeans, that the global average of modern yield premium hides substantial heterogeneity across fields: the 5th, 50th, and 95th percentile are 1.9, 5.5, and 14.9. This heterogeneity is mostly driven by within country-variations. If we adjust the premia by the average in every country by shutting down between-country variations, a remarkable heterogeneity remains in place. A similar pattern holds for other crops, too.

In addition, Figure A.2 in Appendix G.2.1 shows that across countries the average modern potential yield premium does not vary systematically with GDP per capita.[12]

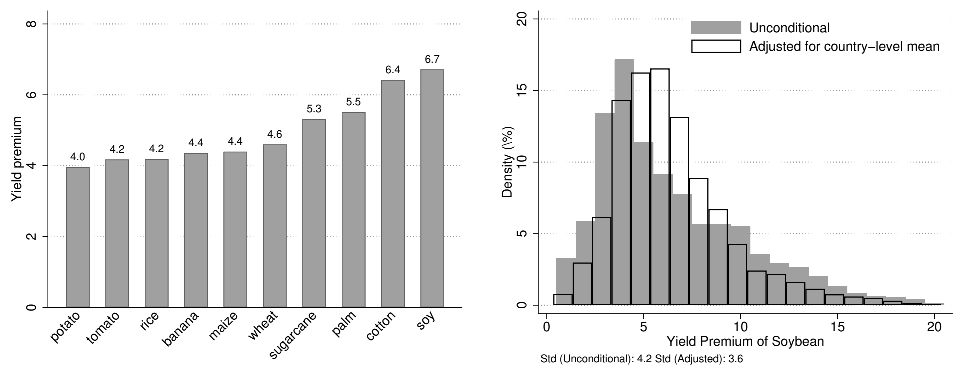
[11]For instance, countries in the Middle East and North Africa (MENA) and in the East Europe have large endowments of raw fertilizers, and, therefore, present a small import share of fertilizers, but imports in these countries account for a large share of their expenditure on farm machinery and pesticides. Import shares of all the input categories are typically the largest among Sub-Saharan African countries and the lowest in North America and East Asia & Pacific. For most European and Latin American countries imports account for about a half of their expenditure on agricultural inputs.

[12]The figure shows (a) unconditional correlation between modern potential yield premia and GDP per capita, and (b) conditional correlation once we control for the level of traditional potential yield. At this point, we only mean to have a first look into the data. The correlation between potential yield premium and GDP per capita, might differ once one controls for composition of crop outputs across countries, within-country heterogeneity

Pattern 3 suggests that shifting production technologies from traditional to modern could substantially increase yields. In addition, our initial inspection of the data indicates that agro-ecological conditions, as captured by the modern potential yield premia, are unlikely to fully account for the large cross-country differences in the cost share of inputs in agriculture. Motivated by these data patterns, we allow technology choices in our framework to depend on both local market conditions related to prices and wages, and agro-ecological conditions reflected by potential yields of crop-technology pairs.

Figure 3: Potential Yield Premium

(a) Average across crops (b) Distribution across field (soybeans)



Notes: Panel (a) shows the average premium of the modern technology across fields in the world. Panel (b) shows the distribution of the premium in the case of soybeans. Adjusted for country mean is computed as the premium at the field level plus the global average premium minus the the country-level average premium.

3 Model

This section develops a general equilibrium model of trade with endogenous choices of crops and technologies in agricultural production. We consider a global economy consisting of many countries. Each country is divided into a discrete number of fields, and each field consists of a continuum of plots. In every plot, agricultural producers face a discrete choice problem of which crop to grow, and with which technology to grow it. Aggregating plot-level choices delivers field-level output of every crop-technology pair, and aggregating field-level output gives country-level output. International trade shapes agricultural productivity around the world due to international crop specialization (output-side mechanism) and due to access to internationally supplied inputs used in modern technologies (input-side mechanism).

in agro-ecological variables, and geographic variables that are responsible for trade openness. Looking ahead, we incorporate these considerations into our model and estimation. We also provide a decomposition exercise in Section 5.4.3 to examine the contribution from variations in modern potential yield premia to variations in technology choices across fields around the world.

Environment. The global economy consists of multiple countries, indexed by i or $n \in \mathcal{N}$. Each country n is endowed by a given supply of labor N_n, land L_n, and raw fertilizer V_n. Consumption combines sector-level bundles of nonagriculture and agriculture. The nonagriculture bundle consists of a single good defined by a singleton $\mathcal{O} \equiv \{0\}$. The agriculture bundle comprises multiple crops, indexed by $k \in \mathcal{K}$. Every crop can be produced using a technology characterized by input and factor intensities. Specifically, technology is either traditional that uses only land and labor, or modern that uses labor, land, and multiple agricultural inputs indexed by $j \in \mathcal{J}$. We denote by $\mathcal{G}$ the set of all goods in the economy consisting of nonagriculture good, agricultural inputs, and crops,

$$\mathcal{G} \equiv \mathcal{O} \cup \mathcal{J} \cup \mathcal{K} = \Big\{ \underbrace{0}_{\text{nonagriculture}}, \underbrace{1, ..., J}_{\text{agricultural inputs } j \in \mathcal{J}}, \underbrace{J+1, ..., J+K}_{\text{crops } k \in \mathcal{K}} \Big\}.$$

A set $\mathcal{F}_n$ of fields f, each with area L_n^f, characterizes the total land in country n, where $L_n \equiv \sum_{f \in \mathcal{F}_n} L_n^f$. Our setup allows for differences in agro-ecological conditions between fields, meaning that land productivities associated with a crop-technology pair (k, τ) are heterogeneous across fields $f \in \mathcal{F}_n$. Labor is homogeneous and freely mobile within countries. Endowments of raw fertilizers are inputs in the production of processed fertilizers.

All goods $g \in \mathcal{G}$ are tradeable, subject to iceberg trade costs: for delivering one unit of g from origin i to destination n, $d_{ni,g} \geq 1$ units must be shipped under triangle inequality. Price of g originated from i and delivered to n is $p_{ni,g} = p_{i,g} d_{ni,g}$, where $p_{i,g}$ denotes the producer price at the location of supply. The price index of g at the location of consumption n, depends on the vector of delivered prices there, $[p_{ni,g}]_i$, and is denoted by $P_{n,g}$. All markets are perfectly competitive.

3.1 Production

Agricultural Technology. Every field $f \in \mathcal{F}_i$ consists of a continuum of plots $\omega \in f$. In each plot ω, agricultural producers choose which crop $k \in \mathcal{K}$ to produce, and with which technology $\tau \in \mathcal{T}$ to produce them. The production technology for crop-technology pair $k\tau$ is given by:

$$Q_{i,k\tau}^f(\omega) = \bar{q}_{k\tau} \left(z_{i,k\tau}^f(\omega) L_{i,k\tau}^f(\omega) \right)^{\gamma_{k\tau}^L} \left(N_{i,k\tau}^f(\omega) \right)^{\gamma_{k\tau}^N} \left(M_{i,k\tau}^f(\omega) \right)^{\gamma_{k\tau}^M}$$

where $\bar{q}_{k\tau}$ is a constant scalar,[13] $z_{i,k\tau}^f(\omega)$ is the land productivity of plot ω for producing crop k using technology τ, and $L_{i,k\tau}^f(\omega)$, $N_{i,k\tau}^f(\omega)$, and $M_{i,k\tau}^f(\omega)$ are the use of land, labor, and material inputs, respectively. Setting up every plot ω for agricultural use requires a fixed cost $z_{i,0}^f(\omega)$ paid in units of nonagriculture good. $\gamma_{k\tau}^N \in [0,1]$, $\gamma_{k\tau}^M \in [0,1]$, and $\gamma_{k\tau}^L = 1 - \gamma_{k\tau}^N - \gamma_{k\tau}^M \in [0,1]$

[13] $\bar{q}_{k\tau} \equiv (\gamma_{k\tau}^L)^{-\gamma_{k\tau}^L} (\gamma_{k\tau}^N)^{-\gamma_{k\tau}^N} (\gamma_{k\tau}^M)^{-\gamma_{k\tau}^M}$

are, respectively, intensity parameters of labor, inputs, and land in production of crop k using technology τ. These intensity parameters characterize technology which are either traditional $\tau = 0$ or modern $\tau = 1$. The bundle of input use $M^f_{i,k\tau}(\omega)$ is a Cobb-Douglas combination of agricultural inputs,

$$M^f_{i,k\tau}(\omega) = \prod_{j \in \mathcal{J}} \left(M^{j,f}_{i,k\tau}(\omega) \right)^{\gamma^{j,M}_k}$$

where $M^{j,f}_{i,k\tau}(\omega)$ is the use of input j and $\gamma^{j,M}_k \in [0,1]$ is the share parameter ($\sum_{j \in \mathcal{J}} \gamma^{j,M}_k = 1$). The price index of the bundle of agricultural inputs in destination i is $m_{i,k} = \prod_{j \in \mathcal{J}} (P_{i,j})^{\gamma^{j,M}_k}$.

By cost minimization, the marginal cost of crop k using technology τ, $c^f_{i,k\tau}(\omega)$, equals

$$c^f_{i,k\tau}(\omega) = \left(\frac{r^f_{i,k\tau}(\omega)}{z^f_{i,k\tau}(\omega)} \right)^{\gamma^L_{k\tau}} \left(w_i \right)^{\gamma^N_{k\tau}} \left(m_{i,k} \right)^{\gamma^M_{k\tau}}$$

where w_i is wage in country i and $r^f_{i,k\tau}(\omega)$ is the gross rental price of plot ω. Since markets are perfectly competitive, net profits in every plot are pushed down to zero. Profit maximization and zero profit condition ensures that $c^f_{i,k\tau}(\omega) = p_{i,k}$. This delivers the gross rental price of land in plot ω (or equivalently, gross returns to plot ω) if assigned to crop-technology $k\tau$,

$$\begin{aligned} r^f_{i,k\tau}(\omega) &= z^f_{i,k\tau}(\omega) h_{i,k\tau} \\ \text{where} \quad h_{i,k\tau} &= p_{i,k} \underbrace{\left(\frac{w_i}{p_{i,k}} \right)^{-\gamma^N_{k\tau}/\gamma^L_{k\tau}} \left(\frac{m_{i,k}}{p_{i,k}} \right)^{-\gamma^M_{k\tau}/\gamma^L_{k\tau}}}_{\widetilde{h}_{i,k\tau}} \end{aligned} \tag{1}$$

Returns to crop-technology $k\tau$ depend on land productivity $z^f_{i,k\tau}(\omega)$, and a price-inclusive term $h_{i,k\tau}$ that summarizes the effect from market prices. The price-inclusive component, $h_{i,k\tau}$, is the product of the output price $p_{i,k}$, and a term denoted by $\widetilde{h}_{i,k\tau}$. This latter term depends on wage and price of material inputs relative to price of output, $w_i/p_{i,k}$ and $m_{i,k}/p_{i,k}$.

The net rental price of land in ω is then the gross returns net of investment costs,

$$z^f_{i,k\tau}(\omega) h_{i,k\tau} - z^f_{i,0}(\omega) P^0_i,$$

where P^0_i is the price index of nonagriculture goods. The optimal allocation in every plot $\omega \in f$ maximizes returns to plot ω by selecting among crop-technology pairs $k\tau$, that is the one with the highest rent or by leaving the plot idle if no crop-technology pair delivers positive net rents,

$$\max \left\{ z^f_{i,k\tau}(\omega) h_{i,k\tau} \text{ for all } \ (k,\tau), \ z^f_{i,0}(\omega) P^0_i \right\}$$

The vector of investment requirement and land productivities, $\mathbf{z}^f_i(\omega) \equiv [z^f_{i,k\tau}(\omega) \quad \text{for all}$

$(k,\tau) \in \mathcal{K} \times T$, $z^f_{i,0}(\omega)]$ is randomly drawn across plots $\omega \in f$ from a nested Fréchet distribution,

$$\Pr(\mathbf{z}^f_i(\omega) \leq \mathbf{z}^f_i) = \exp\left\{ -\bar{\phi}\left[\left(\Gamma_0(z^f_{i,0})\right)^{-\theta_1} + \sum_{k\in\mathcal{K}}\left(\Gamma_k(\mathbf{z}^f_{i,k})\right)^{-\theta_1}\right]\right\}$$

$$\text{where} \quad \Gamma_0(z^f_{i,0}) = \left(\frac{z^f_{i,0}}{a^f_{i,0}}\right), \quad \Gamma_k(\mathbf{z}^f_{i,k}) = \left[\sum_{\tau\in\mathcal{T}}\left(\frac{z^f_{i,k\tau}}{a^f_{i,k\tau}}\right)^{-\theta_2}\right]^{-\frac{1}{\theta_2}} \text{ for all } k \in \mathcal{K}$$

Here, $\bar{\phi} \equiv \left[\Gamma(1-1/\theta_1)\right]^{-\theta_1}$ is a normalization to ensure that $\mathbb{E}[z^f_{i,0}(\omega)] = a^f_{i,0}$, and $\mathbb{E}[z^f_{i,k\tau}(\omega)] = a_{i,k\tau}$. Our formulation generalizes a standard Fréchet distribution as the one in Eaton and Kortum (2002) by relaxing the assumption that productivity draws across alternatives are independent. We achieve this extension by building on tools from the literature on discrete choice based on generalized extreme value distributions (McFadden, 1981). We present a detailed derivation in the appendix, and explain the intuition below.

This generalized Fréchet distribution allows productivity draws to be correlated in a structured way. In the upper nest, θ_1 controls the dispersion of land productivity draws across crops. The higher θ_1, the less heterogeneous the land productivity draws across crops within a field. Consequently, producers will be more responsive in substituting across crops when relative returns to crops change. In the lower nest, θ_2 controls the dispersion of productivity draws across technologies within every crop. The larger θ_2 relative to θ_1 is, the larger the correlation between draws are across technologies within a crop. Given a choice of crop, at a higher θ_2, producers are more responsive in adopting a technology when returns to that technology rise.

Consider the case with two crops, say corn and wheat. In the case where $\theta_2 > \theta_1 > 1$, productivity draws between corn-traditional and corn-modern are more similar compared to draws between corn and wheat. Setting $\theta_1 = \theta_2$ brings the model back to a one-nest Fréchet distribution where the correlation between draws across technologies within a crop is not different from that across crops. In that case, draws between corn-modern and corn-traditional are equally dissimilar to draws between corn-modern and wheat-traditional, or corn-modern and wheat-modern.

Agricultural Output and Land Allocation. For every field f, we denote the fraction of land allocated to crop-technology $k\tau$ by $\pi^f_{i,k\tau}$. Furthermore, let $\alpha^f_{i,k}$ be the fraction of land allocated to crop k, and $\alpha^f_{i,k\tau}$ be the fraction of land within crop k allocated to technology τ. The land shares are given by

$$\pi^f_{i,k\tau} = \alpha^f_{i,k} \times \alpha^f_{i,k\tau} \tag{2}$$

where

$$\alpha^f_{i,k\tau} = \frac{\left(a^f_{i,k\tau} h_{i,k\tau}\right)^{\theta_2}}{(H^f_{i,k})^{\theta_2}} \tag{3}$$

$$\alpha^f_{i,k} = \frac{(H^f_{i,k})^{\theta_1}}{(a^f_{i,0} P^0_i)^{\theta_1} + \sum_{k\in\mathcal{K}} (H^f_{i,k})^{\theta_1}}. \tag{4}$$

The aggregate return to crop k, $H^f_{i,k}$, equals

$$H^f_{i,k} = \left[\sum_{\tau\in\mathcal{T}} \left(a^f_{i,k\tau} h_{i,k\tau}\right)^{\theta_2}\right]^{\frac{1}{\theta_2}} \tag{5}$$

Equations (2)–(5) connect the dispersion parameters of the Fréchet distribution to elasticities of land use. Specifically, θ_2 appears as the elasticity of substitution across technologies within a crop choice, and θ_1 as the elasticity of substitution in land use across crops (and non-cropland). The opportunity cost of agriculture production, $a^f_{i,0} P^0_i$, pins down the total share of cropland. Within the cropland, land share of crop k increases in its average returns $H^f_{i,k}$, with the extent of the relationship governed by θ_1. Within the land allocated to crop k, the land share of technology τ rises in average returns to technology τ, $a^f_{i,k\tau} h_{i,k\tau}$, with the extent of the relationship disciplined by θ_2.

Let $\Omega^f_{i,k\tau}$ be the set of plots ω in field f to which crop-technology $k\tau$ is optimally allocated. Conditional on $\omega \in \Omega^f_{i,k\tau}$, the average productivity of crop-technology $k\tau$ in field f equals

$$\mathbb{E}[z^f_{i,k\tau}(\omega) \mid \omega \in \Omega^f_{i,k\tau}] = a^f_{i,k\tau} (\alpha^f_{i,k})^{-\frac{1}{\theta_1}} (\alpha^f_{i,k\tau})^{-\frac{1}{\theta_2}}. \tag{6}$$

The conditional mean productivity of crop-technology $k\tau$ is greater than the unconditional mean productivity, $\mathbb{E}[z^f_{i,k\tau}(\omega)] = a^f_{i,k\tau}$. To see this, suppose that the share of land allocated to corn rises due to an increase in the relative price of corn. This is achievable by adding infra-marginal plots that have lower land productivity for corn production. As a result, the mean land productivity of corn falls. This dampening effect of selection on average land productivity is governed by θ_1 along the dimension of crop choices, and by θ_2 along the dimension of technology.

With equation (6), we can now derive output quantities by putting together three observations. First, the optimal allocation requires each plot $\omega \in f$ either not to be used (i.e., to stay idle) or to be used for the production of a single crop-technology pair. Second, according to equation (1), the return to land for plot ω equals $p_{i,k} \widetilde{h}_{i,k\tau} z^f_{i,k\tau}(\omega)$. Third, since a fraction $\gamma^L_{k\tau}$ of gross output is paid to land, hence $\gamma^L_{k\tau} p_{i,k} Q^f_{i,k\tau}(\omega) = p_{i,k} \widetilde{h}_{i,k\tau} z^f_{i,k\tau}(\omega)$. Combining these three points,

$$Q^f_{i,k\tau}(\omega) = \begin{cases} (\gamma^L_{k\tau})^{-1}\widetilde{h}_{i,k\tau} z^f_{i,k\tau}(\omega), & \omega \in \Omega^f_{i,k\tau} \\ 0, & \omega \notin \Omega_{i,k\tau} \end{cases} \tag{7}$$

At the field level, aggregate output of crop k using technology τ in field f within country i, $Q^f_{i,k\tau}$, equals land use, $\pi^f_{i,k\tau} L^f_i$, times average production across plots, $\mathbb{E}[Q^f_{i,k\tau}(\omega) \mid \omega \in \Omega^f_{i,k\tau}]$. Using equations (2), (6), (7),

$$\begin{aligned} Q^f_{i,k\tau} &= \pi^f_{i,k\tau} L^f_i \times \mathbb{E}\Big[Q^f_{i,k\tau}(\omega) \mid \omega \in \Omega^f_{i,k\tau}\Big] \\ &= L^f_i (\gamma^L_{k\tau})^{-1}\widetilde{h}_{i,k\tau} a^f_{i,k\tau} (\alpha^f_{i,k})^{\frac{\theta_1 - 1}{\theta_1}} (\alpha^f_{i,k\tau})^{\frac{\theta_2 - 1}{\theta_2}} \end{aligned} \tag{8}$$

Notice that production is constant-returns-to-scale at the level of plots, but decreasing-returns-to-scale at the level of fields. The reason is the selection margin that is operative in the aggregation over plots, as we explained above in discussing equation (6). Specifically, field-level output $Q^f_{i,k\tau}$ is homogeneous of degree $(\theta_1 - 1)/\theta_1$ w.r.t. crop-specific land use, and of degree $(\theta_2 - 1)/\theta_2$ w.r.t. technology-specific land use per crop. Aggregate output of crop k in country i is then given by:

$$Q_{i,k} = \sum_{f \in \mathcal{F}_i} \sum_{\tau \in \mathcal{T}} Q^f_{i,k\tau}. \tag{9}$$

Lastly, aggregate quantity of nonagriculture good that is required for setting up plots is denoted by S_i and equals

$$S_i = \sum_{f \in \mathcal{F}_i} L^f_i a^f_{i,0} \Big[1 - \Big(1 - \sum_{k \in \mathcal{K}} \alpha^f_{i,k}\Big)^{(\theta_1 - 1)/\theta_1}\Big]. \tag{10}$$

Nonagricultural Technology. Production of processed fertilizer, denoted by $v \in \mathcal{J}$, is linear in the domestic endowments of raw fertilizers, V_i. The production of every other non-crop good $g = \{$nonagriculture $(g = 0)$, non-fertilizer inputs $(g \in \mathcal{J}, g \neq v)\}$ employs labor $N_{i,g}$ featuring constant-returns-to-scale with labor productivity $A_{i,g}$.

3.2 Consumption

Every good $g \in \mathcal{G}$ is differentiated by the origin of production. Consumers purchase varieties of every good g from different origins according to CES preferences with elasticity of substitution $\sigma_g > 0$ and demand shifters $b_{ni,g}$. Accordingly, the share of expenditure by country n on good $g \in \mathcal{G}$ from origin i is:

$$\lambda_{ni,g} = \frac{b_{ni,g}(p_{i,g} d_{ni,g})^{1-\sigma_g}}{(P_{n,g})^{1-\sigma_g}} \tag{11}$$

The agricultural consumption bundle, on its turn, aggregates the consumption of all crops according to a CES function with elasticity of substitution κ and demand shifters $b_{n,k}$. The share of expenditure by country n on crop k relative to aggregate agriculture expenditure equals:

$$\beta_{n,k} = \frac{b_{n,k}(P_{n,k})^{1-\kappa}}{(P_n^1)^{1-\kappa}} \tag{12}$$

Lastly, the final good aggregates over the consumption bundles of nonagriculture ($s = 0$) and agriculture (s =1) according to a nonhomothetic CES with an elasticity of substitution η, income elasticities ε^s, and demand shifters b_n^s. The share of expenditure by country n on sector-level bundles of nonagriculture and agriculture equals:

$$\beta_n^s = \frac{b_n^s(E_n/P_n)^{\varepsilon^s-1}(P_n^s)^{1-\eta}}{(P_n)^{1-\eta}} \tag{13}$$

where E_n is total expenditure in country n. If $\eta < 1$, agriculture and nonagriculture are complements; otherwise, they are substitutes. Agriculture is a necessity if $\varepsilon^0 > \varepsilon^1$. When $\varepsilon^0 = \varepsilon^1 = 1$, the system collapses to CES preferences. Price indices are:

$$P_{n,g} = \left[\sum_{i\in\mathcal{N}} b_{ni,g}(p_{i,g}d_{ni,g})^{1-\sigma_g}\right]^{\frac{1}{1-\sigma_g}} \tag{14}$$

$$P_n^s = \begin{cases} P_{n,0}, & \text{if } s = 0 \\ \left[\sum_{k\in\mathcal{K}} b_{n,k}(P_{n,k})^{1-\kappa}\right]^{\frac{1}{1-\kappa}}, & \text{if } s = 1 \end{cases} \tag{15}$$

$$P_n = \left[\sum_{s\in\{0,1\}} b_n^s(E_n/P_n)^{\varepsilon^s-1}(P_n^s)^{1-\eta}\right]^{\frac{1}{1-\eta}} \tag{16}$$

The price effects operate via substitutions in the upper tier between nonagriculture and agriculture through $(P_n^s/P_n)^{1-\eta}$, in the middle tier between crops (e.g. wheat vs corn) within agriculture through $(P_{n,k}/P_n^1)^{1-\kappa}$, and in the lower tier between varieties of different origins within a crop (e.g. US corn vs Brazilian corn) through $(p_{ni,k}/P_{n,k})^{1-\sigma_k}$. The income effect operates through $(E_n/P_n)^{\varepsilon^s-1}$ in the upper tier between nonagriculture ($s = 0$) and agriculture ($s = 1$). Note that P_n is the cost-of-living index, and welfare or aggregate real consumption thus equals $C_n = E_n/P_n$.[14]

[14]The utility derived from final consumption, C_n, is defined implicitly according to $\sum_{s\in\{0,1\}}\left(b_n^s\right)^{\frac{1}{\eta}}\left(C_n\right)^{\frac{\varepsilon^s-\eta}{\eta}}\left(C_n^s\right)^{\frac{\eta-1}{\eta}} = 1$. The pair of equations (16) and (13) characterize the non-homotheticity in demand, i.e. how the price index and expenditure shares vary by income. In the empirically relevant case, where $\varepsilon^0 > \varepsilon^1$, a rise in welfare, E_n/P_n, is associated with an increase in the share of expenditure on nonagriculture, β_n^1. See Comin, Lashkari, and Mestieri (2015) for details.

3.3 General Equilibrium

Goods market clearing for nonagriculture, agricultural inputs $j \in \mathcal{J}$, and crops $k \in \mathcal{K}$ require supply at the origin country to equal world demand,

$$
\begin{aligned}
p_{i,0}Q_{i,0} &= \sum_{n\in\mathcal{N}} \lambda_{ni,0}\beta_n^0 E_n + P_i^0 S_i & (17)\\
p_{i,j}Q_{i,j} &= \sum_{f\in\mathcal{F}_i}\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}} \lambda_{ni,j}\gamma_k^{j,M}\gamma_{k1}^M p_{n,k}Q_{n,k1}^f & (18)\\
p_{i,k}Q_{i,k} &= \sum_{n\in\mathcal{N}} \lambda_{ni,k}\beta_{n,k}\beta_n^1 E_n & (19)
\end{aligned}
$$

Labor market clearing in every country i requires labor supply N_i to equal labor demand from agriculture and elsewhere,

$$
N_i = \underbrace{\frac{1}{w_i}\left[\sum_{g\in\mathcal{O}\cup\mathcal{J},g\neq v} p_{i,g}Q_{i,g}\right]}_{\text{nonagriculture employment},N_i^0} + \underbrace{\frac{1}{w_i}\left[\sum_{k\in\mathcal{K}}\sum_{f\in\mathcal{F}_i}\sum_{\tau\in\mathcal{T}} \gamma_{k\tau}^N p_{i,k}Q_{i,k\tau}^f\right]}_{\text{agriculture employment},N_i^1} \tag{20}
$$

Finally, total expenditure in country i, E_i, equals the sum of factor rewards,

$$
E_i = \sum_{k\in\mathcal{K}}\sum_{f\in\mathcal{F}_i}\sum_{\tau\in\mathcal{T}} (\gamma_{k\tau}^N + \gamma_{k\tau}^L)p_{i,k}Q_{i,k\tau}^f - P_i^0 S_i + \sum_{g\in\mathcal{O}\cup\mathcal{J}} p_{i,g}Q_{i,g} \tag{21}
$$

The first term net of the second term in the RHS equals payments to labor and land in agriculture. The third term is payments to labor in nonagriculture and agricultural inputs as well as revenues from fertilizer sales. Equations 17 -21 guarantee that trade is balanced and land markets clear.

We close the layout of our model by defining the global economy and general equilibrium.

Definition 1. For all countries $n, i \in \mathcal{N}$, fields $f \in \mathcal{F}_n$, goods $g \in \mathcal{G}$ consisting of nonagriculture, agricultural inputs $j \in \mathcal{J}$, crops $k \in \mathcal{K}$, sectors $s \in \{0, 1\}$, and technologies $\tau \in \mathcal{T}$, a **global economy** is characterized by endowments $\mathcal{E} \equiv \{L_n^f, N_n, V_n\}$, supply parameters $\Omega_S \equiv \{\theta_1,\ \theta_2,\ \gamma_{k\tau}^L,\ \gamma_{k\tau}^M, \gamma_{k\tau}^N, \gamma_k^{j,M},\ a_{n,0}^f,\ a_{n,k\tau}^f\}$, and demand parameters $\Omega_D \equiv \{\varepsilon^0, \varepsilon^1, \eta, \kappa, \sigma_g, b_n^s, b_{n,k}, b_{ni,g}, d_{ni,g}, A_{n,g}\}$.[15]

Definition 2. Given a global economy characterized by $\{\mathcal{E}, \Omega_S, \Omega_D\}$, a **general equilibrium** consists of prices $\{p_{n,g}\}$ in all countries $n \in \mathcal{N}$ and for all goods $g \in \mathcal{G}$, such that equations 1–21 hold.

[15]Here, Ω_S summarizes parameters of agricultural production function, and as such, by supply we mean that of agricultural outputs. This classification greatly simplifies our exposition of the estimation of the model in Section 5.

4 Discussion: Trade, Technology, and Productivity

This section discusses the interplay between trade, technology and agricultural productivity in our model. First, we derive and discuss the production possibility frontiers (PPF) implied by our generalized Fréchet distribution, which will be critical for the strategy that we use to bring our model to FAO-GAEZ data. Second, we show how our model generates a new source of gains from trade that arises from the interaction between technology and trade in intermediate inputs. In doing so, we benchmark our analytical result with Arkolakis, Costinot, and Rodriguez-Clare (2012).[16]

4.1 The Production Possibility Frontier in each Field

In our framework, crop quantities in every field are the endogenous outcomes of the aggregation of discrete choices over a continuum of plots. To better understand how the generalized Fréchet distribution govern aggregate choices, we study an equivalent maximization problem in which agricultural producers allocate land efficiency units to crop-technology pairs subject to a production possibility frontier (PPF). For a given field f in country i, consider this maximization problem:

$$\max_{\{\widetilde{L}^f_{i,k\tau}\}_{k,\tau}\ ,\ \{\widetilde{L}^f_{i,k}\}_k} \quad \sum_{\tau\in\mathcal{T}}\sum_{k\in\mathcal{K}} h_{i,k\tau}\widetilde{L}^f_{i,k\tau}$$

$$\text{subject to} \qquad \left[\sum_{\tau\in\mathcal{T}}(\widetilde{L}^f_{i,k\tau}/a^f_{i,k\tau})^{\frac{\theta_2}{\theta_2-1}}\right]^{\frac{\theta_2-1}{\theta_2}} \leq \widetilde{L}^f_{i,k} \tag{22}$$

$$\left[\sum_{k\in\mathcal{K}}(\widetilde{L}^f_{i,k})^{\frac{\theta_1}{\theta_1-1}}\right]^{\frac{\theta_1-1}{\theta_1}} \leq L^f_i, \tag{23}$$

where $\widetilde{L}^f_{i,k\tau}$ and $\widetilde{L}^f_{i,k}$ are efficiency units of land at the level of crop-technology $k\tau$, and crop k. The agricultural producer maximizes the sum of returns across uses of land, $\sum_{\tau\in\mathcal{T}}\sum_{k\in\mathcal{K}} h_{i,k\tau}\widetilde{L}^f_{i,k\tau}$, subject to the PPF (equations 22, 23), i.e., she chooses $\widetilde{L}^f_{i,k\tau}$ and $\widetilde{L}^f_{i,k}$ given price-inclusive terms $h_{i,k\tau}$ described by equation (1), technology coefficients $a^f_{i,k\tau}$, and land endowment L^f_i.[17]

We illustrate this problem with diagrams for two crops, which we call rice and wheat. To save on notation, we drop country and field indicators. Figure 4 presents the production possibility frontiers in two tiers. The lower tier, represented by Panel (b), reflects substitution possibilities across technologies within a crop, and the upper tier, represented by Panel (a), disciplines

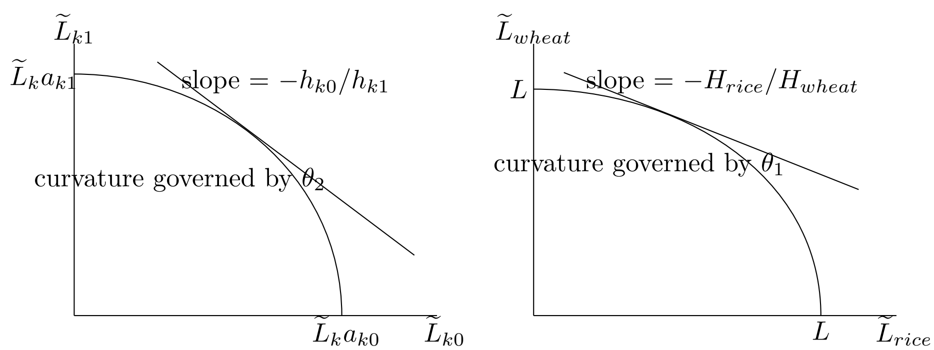
[16] See Appendix Section C for a detailed derivation of the results in this section.

[17] Two comments come in order. First, for the sake of exposition, we have set the value of the outside option at zero. Second, efficiency units $\widetilde{L}^f_{i,k\tau}$ immediately deliver production quantities $Q^f_{i,k\tau}$ according to: $Q^f_{i,k\tau} = (1/\gamma^L_{k\tau})\widetilde{h}_{i,k\tau}\widetilde{L}^f_{i,k\tau}$, where, as defined by equation (1), $\widetilde{h}_{i,k\tau} = (w_i/p_{i,k})^{-\gamma^N_{k\tau}/\gamma^L_{k\tau}}(m_{i,k}/p_{i,k})^{-\gamma^M_{k\tau}/\gamma^L_{k\tau}}$.

substitution possibilities between crops.

Figure 4: Production Possibility Frontier

(a) Between technologies within crop k (b) Between crops



Notes: Panel (a) shows the lower-tier production possibility frontier within crop k between the two technologies, 1 as modern and 0 as traditional. Panel (b) shows the upper-tier production possibility frontier between the two crops, rice and wheat. $\{\widetilde{L}_{k\tau}, \widetilde{L}_k\}$ are in units of land efficiency. In Panel (a) the slope of the curve is proportional to $-(\widetilde{L}_{k0}/\widetilde{L}_{k1})^{1/(\theta_2-1)}$, and the maximum quantity of $\widetilde{L}_{k\tau}$ is $a_{k\tau}\widetilde{L}_k$ where $\widetilde{L}_k$ is the choice variable in the upper tier. In Panel (b), the slope of of the curve equals $-(\widetilde{L}_{rice}/\widetilde{L}_{wheat})^{1/(\theta_1-1)}$, and $H_k = \left[\sum_\tau (a_{k\tau}h_{k\tau})^{\theta_2}\right]^{\frac{1}{\theta_2}}$ for $k \in \{rice, wheat\}$. The maximum quantity of $\widetilde{L}_k$ is the entire field area, L.

Panel (a) shows for every crop k the optimal choices of output in units of land efficiency using traditional ($\tau = 0$) and modern ($\tau = 1$) technologies. The maximum that could be achieved if all resources for the production of crop k were allocated to technology τ is given by $a_{k\tau}\widetilde{L}_k$. This maximum value depends on technology coefficients, $a_{k\tau}$, as well as aggregate efficiency units allocated to crop k, $\widetilde{L}_k$, which is a choice variable in the upper tier —In Section 5.2, we show how we exploit the productivity measures from FAO-GAEZ to recover $a_{k\tau}$—. The slope of the frontier curve at point $(\widetilde{L}_{k0}, \widetilde{L}_{k1})$ is proportional to $(\widetilde{L}_{k0}/\widetilde{L}_{k1})^{1/(\theta_2-1)}$, that is governed by θ_2. The smaller θ_2, the greater the curvature, the less elastic choices of technology in response to a change in market conditions.[18] The slope of the iso-value line in turn equals h_{k0}/h_{k1}, which incorporates the effects from relative wages and input prices adjusted by relative labor and input intensities.

Panel (b) shows the upper tier of production choices that represents the substitution possibilities between rice and wheat. The slope of the frontier at point $(\widetilde{L}_{rice}, \widetilde{L}_{wheat})$ equals $(\widetilde{L}_{rice}/\widetilde{L}_{wheat})^{1/(\theta_1-1)}$, that is governed by θ_1. A smaller θ_1 means more curvature, hence lower sensitivity in substitution across crops if relative prices change.[19] In addition, the slope of the iso-value line is $(-H_{rice}/H_{wheat})$. Reproducing H_k from equation (5), it is a generalized mean

[18] In one extreme where $\theta_2 \to \infty$, the frontier is a straight line, and the problem has a corner solution reflecting that choices of technology can be extremely sensitive to relative prices. In the other extreme where $\theta_2 \to 1$, the frontier collapses to a right angle, and the optimal choice becomes insensitive to prices.

[19] Similarly, if $\theta_1 \to \infty$, the producer problem has a corner solution, and if $\theta_1 \to 1$, the optimal choice of $(\widetilde{L}_{rice}, \widetilde{L}_{wheat})$ becomes insensitive to price changes.

of $a_{k\tau}h_{k\tau}$ across technologies within every crop, $H_k = \left[\sum_\tau (a_{k\tau}h_{k\tau})^{\theta_2}\right]^{\frac{1}{\theta_2}}$. Therefore, crop-level returns that are taken into account in the upper tier depend on optimal decisions made in the lower tier. Moreover, the maximum efficiency units of land that can be allocated to crop k equals total land area. This maximum value is not greater than total land area because the selection margin raises average land productivity only if a fraction of land, not the entire area of it, is allocated to a crop.[20]

4.2 The Gains from Trade

We now study how the interaction between access to foreign inputs and technology adoption introduces a novel source of welfare gains from trade. To focus on the main forces at work, in this section, we simplify our model along two dimensions. First, we assume Cobb-Douglas preferences between goods and CES preferences within goods, meaning that the share of expenditure on nonagriculture and agriculture, β_n^0 and β_n^1, and on every crop k within agriculture, $\beta_{n,k}$, are here exogenously fixed compared to (12)-(13), but trade shares, $\lambda_{ni,g}$, are still given by equation (11). Second, we assume no use of labor in agriculture.

Consider a shock to trade costs $\{d_{ni,g}\}$. For a generic variable x in the baseline, let x' be its value in the new equilibrium, and $\hat{x} \equiv x'/x$. The change to welfare (real consumption, $\hat{C}_i$) in response to changes to trade cost parameters ($\{\hat{d}_{ni,g}\}$) becomes:

$$\hat{C}_i = \underbrace{\left(\hat{\rho}_{i,0}\left(\hat{\lambda}_{ii,0}\right)^{\frac{1}{\sigma_0-1}}\right)^{-\beta_i^0} \prod_k \left(\hat{\rho}_{i,k}\left(\hat{\lambda}_{ii,k}\right)^{\frac{1}{\sigma_k-1}}\right)^{-\beta_i^1\beta_{i,k}}}_{\text{nonag and ag trade (ACR)}} \underbrace{\left[\sum_f \rho_{i,k}^f (\hat{\alpha}_{i,k}^f)^{\frac{\theta_1-1}{\theta_1}} (\hat{\alpha}_{i,k0}^f)^{\frac{-1}{\theta_2}}\right]^{\beta_i^1\beta_{i,k}}}_{\text{ag productivity (New)}} \tag{24}$$

where $\hat{\rho}_{i,0}$ and $\hat{\rho}_{i,k}$ are changes to value added share of nonagriculture and crop k, and $\rho_{i,k}^f$ is the baseline value added share of field f within crop k. Equation (24) shows the sufficient set of information required to calculate welfare gains from any change to trade costs. Notice that, if all land is fully allocated to a single crop-technology pair, i.e., if $\hat{\alpha}_{i,k}^f = \hat{\alpha}_{i,k0}^f = 1$, equation (24) collapses to the standard formula for welfare change in a trade model with multiple-sectors, as discussed in Costinot and Rodríguez-Clare (2014). Here, the reallocation of land across crops and technologies matters for real consumption.

To focus on the role of technology adoption, consider a pared down version of our model

[20]The shadow prices of this aggregate problem replicate land rents (i.e. land returns) predicted by our microfounded model. Specifically, we derive in the appendix that the Lagrange multiplier associated with the slack constraints (22) and (23) are respectively given by H_k and $[\sum_k H_k^{\theta_1}]^{1/\theta_1}$. That is, the shadow price of the land allocated to crop k equals H_k, which is the average returns to land used for production of crop k, and the shadow price of the entire cropland equals $[\sum_k H_k^{\theta_1}]^{1/\theta_1}$, which is precisely the average rents of cropland. For full derivations of this aggregate problem, see Appendix (C.5).

in which utility solely depends on food consumption and agriculture consists of a single crop.[21] Consider also a country where agricultural inputs are entirely imported. This means that in autarky country i is restricted to domestic varieties for consumption, and traditional technologies for production. In this stylized model, the gains from trade in country i, defined as the percentage loss in real income from raising trade costs to infinity, is

$$G_i = 1 - \underbrace{(\lambda_{ii})^{\frac{1}{\sigma-1}}}_{\text{trade}} \underbrace{(\bar{\alpha}_{i,0})^{\frac{1}{\theta_2}}}_{\text{technology}}, \tag{25}$$

where λ_{ii} is the baseline domestic share of expenditure on agriculture, and $\bar{\alpha}_{i,0}$ is a weighted average share of the domestic land allocated to traditional technology, $\bar{\alpha}_{i,0} \equiv \left[\sum_f \rho_i^f \left(\alpha_{i,0}^f\right)^{\frac{1}{\theta_2}}\right]^{\theta_2}$. Equation (25) underscores two sources of gains from trade: A classic channel, $(\lambda_{ii})^{\frac{1}{\sigma-1}}$, that measures the gains from access to foreign consumption varieties, and a new channel, $(\bar{\alpha}_{i,0})^{\frac{1}{\theta_2}}$, that reflects how access to foreign inputs unlocks the use of modern agricultural technologies. The gains from this new channel is summarized by the baseline share of land using the traditional technology ($\bar{\alpha}_{i,0}$), and the elasticity of substitution in production across technologies (θ_2). The smaller $\bar{\alpha}_{i,0}$ or θ_2, the larger these gains. Compared to the classic one-sector formula, i.e. $G_i = 1 - (\lambda_{ii})^{1/(\sigma-1)}$, equation (25) delivers unambiguously larger gains from trade.

5 Taking the Model to Data

The estimation of our model consists of two steps. We first estimate demand-side parameters, Ω_D (for parameters included in Ω_D, see Definition 1) using country-level data on production and trade. We then estimate supply-side parameters of agriculture, Ω_S, employing our field-level data on potential yields and country-level data on agricultural production. After presenting our estimation procedure, we discuss the identification of our supply side parameters. We then close this section by presenting the estimation results, model fit, and sources of spatial variations in technology choices.

[21] We focus on the technology-related channel since the crop-related channel has been studied elsewhere. To see it, let $\theta_2 \to \infty$, then the agriculture productivity channel is given by: $\left[\sum_f \rho_{i,k}^f (\hat{\alpha}_{i,k}^f)^{\frac{\theta_1-1}{\theta_1}}\right]^{\beta_i^1 \beta_{i,k}}$. This expression shows that a reallocation of land across crops matters for welfare because θ_1 is finite, meaning that crop production features decreasing returns to scale at the level of fields. The analogue in the trade literature is where production features economies of scale and/or labor is imperfectly mobile across industries. For a recent discussion, see the gains from trade formula in Kucheryavyy, Lyn, and Rodríguez-Clare (2016), Galle, Rodríguez-Clare, and Yi (2017), and Farrokhi and Soderbery (2020).

5.1 Demand-side parameters

Demand for Agricultural Goods. We estimate the demand for agricultural goods as in Costinot, Donaldson, and Smith (2016). First, based on equation (11), we estimate the elasticity of substitution between crop-varieties (σ_k) using:

$$\log\left(\frac{X_{ni,k}}{X_{n,k}}\right) = \delta_{n,k} + (1-\sigma_k)\log p_{i,k} + \epsilon_{ni,k}.$$

Here, $X_{ni,k}$ is the purchases of n from country i of crop k, $X_{n,k}$ is total purchases of country n of crop k, $\delta_{n,k} \equiv -\log[\sum_i b_{ni,k}(p_{i,k}d_{ni,k})^{1-\sigma_k}]$ is an importer-crop fixed effect, and $\epsilon_{ni,k} = \log b_{ni,k}d_{ni,k}^{1-\sigma_k}$ is a residual. We set $\sum_{i=1}^{N}\epsilon_{ni,k} = 0$ (without loss of generality), recover $b_{ni,k}d_{ni,k}^{1-\sigma_k}$ from $\epsilon_{ni,k}$, and estimate a common elasticity of substitution between crop varieties ($\sigma_k = \sigma$). Due to potential correlations between demand shocks and prices, we instrument $\log p_{i,k}$ with the average of potential yields across fields of the exporting country. With estimates of σ_k and $b_{ni,k}d_{ni,k}^{1-\sigma_k}$, we construct $P_{n,k}$ according to equation (15). Using equation (12), we then estimate the elasticity of substitution between crops (κ) based on:

$$\log\left(\frac{X_{n,k}}{X_n^1}\right) = \delta_n + (1-\kappa)\log P_{n,k} + \epsilon_{n,k},$$

where X_n^1 is aggregate purchases of all crops, $\delta_n = (1-\kappa)\log P_n^1$ is a country fixed effect, $\epsilon_{n,k} = \log b_{n,k}$ is a residual, and without loss of generality, $\sum_{k\in\mathcal{K}}\epsilon_{n,k} = 0$. Again, to address potential endogeneity issues, we instrument $\log P_{n,k}$ using the average potential yield of each pair of country-crop. We recover $b_{n,k}$ from residuals $\epsilon_{n,k}$.

Demand for Nonagricultural Goods. We set $\sigma_g = 4$ for non-agriculture good and for agricultural inputs based on the literature.[22] For $g = \{\text{nonagriculture, pesticides, farm machinery}\}$, we estimate:

$$\log\left(\frac{X_{ni,g}}{X_{n,g}}\right) - (1-\sigma_g)\log w_i = \delta_{n,g} + \delta_{i,g} + \epsilon_{ni,g}, \tag{26}$$

where $\delta_{n,g} = (1-\sigma_g)\log P_{n,g}$ is a destination fixed effect, $\delta_{i,g} = (1-\sigma_g)\log A_{i,g}$ is an origin fixed effect, and $\epsilon_{ni,g} = \log(b_{ni,g}d_{ni,g}^{1-\sigma_g})$ is the residual. We recover $b_{ni,g}d_{ni,g}^{1-\sigma_g}$ from $\epsilon_{ni,g}$ and $A_{i,g}$ from $\delta_{n,g}$. For $g = \text{fertilizers}$, we estimate the expression above without $\delta_{i,g}$, substitute $\log w_i$ by $\log p_{i,g}$ and recover $b_{ni,g}d_{ni,g}^{1-\sigma_g}$ from residuals.

Upper-tier Demand Parameters. We set income elasticities of nonagriculture and agriculture goods at $\varepsilon^0 = 1.5$ and $\varepsilon^1 = 0.5$, and the substitution elasticity between agriculture

[22] For example, see Simonovska and Waugh (2014) and Imbs and Mejean (2015).

and nonagriculture at $\eta = 0.5$ according to Comin, Lashkari, and Mestieri (2015).[23] These parameters imply that agriculture is a necessity whereas nonagriculture is a luxury, and that agriculture and nonagriculture are complements. Given (η, ε^0, ε^1), we recover demand shifters (b_n^0, b_n^1) using expressions (16) and (13). To do so, we use model-implied price indexes, (P_n^0, P_n^1), which we obtain after fully calibrating the model.

5.2 Supply-Side Parameters

We now turn to the supply side parameters, Ω_S. We define $\tilde{\gamma}^L \equiv \gamma_0^L/\gamma_1^L$ and estimate $\Theta = \{\theta_1, \theta_2, \tilde{\gamma}^L\}$, subject to a calibration problem that sets $\Gamma \equiv \Omega_S/\Theta = \{a_{i,0}^f,\ a_{i,k\tau}^f,\ \gamma_{k\tau}^N,\ \gamma_{k\tau}^L,\ \gamma_k^M,\ \gamma_k^{j,M}\}_{k,\tau}$. Our estimation procedure can be thought of as a two-layer problem. In the *inner* problem, we take Θ as given, and calibrate Γ so that the general equilibrium of the model matches a number of targets. In the *outer* problem, we search for $\widehat{\Theta}$ to minimize the distance between aggregate moments in the data and their simulated counterparts in the model. We briefly present our procedure here, relegating a full step-by-step description to the appendix.

Calibration (Inner Problem). To calibrate productivity shifters, $a_{i,k\tau}^f$, we exploit potential yield data from FAO-GAEZ. By construction, potential yield, $y_{i,k\tau}^{f,data}$, equals the average land productivity in field f if the entire area of the field were allocated to crop k using technology τ. In our model, the corresponding yield value is obtained by setting $\alpha_{i,k}^f = \alpha_{i,k\tau}^f = 1$ in equation (8) and by dividing the resulting equation by L_i^f, which gives $(\gamma_{k\tau}^L)^{-1}\widetilde{h}_{ik\tau}a_{i,k\tau}^f$. Since potential yields data do not reflect local market conditions, we assume $\widetilde{h}_{ik\tau}$ to be the same across countries ($\widetilde{h}_{ik\tau} = \widetilde{h}_{k\tau}$).[24] Given these remarks, we can connect the unobserved productivity shifters $a_{i,k\tau}^f$ to observed potential yields $y_{i,k\tau}^{f,data}$ based on $y_{i,k\tau}^{f,data} = (\gamma_{k\tau}^L)^{-1}\widetilde{h}_{k\tau}a_{i,k\tau}^f$. Using this relationship, we express $a_{i,k\tau}^f$ as:

$$a_{i,k\tau}^f = \delta_{k\tau} y_{i,k\tau}^{f,data} \tag{27}$$

where $\delta_{k\tau} \equiv \gamma_{k\tau}^L/\widetilde{h}_{k\tau}$ is an unobserved scale parameter. Hence, all we need to recover is a scale parameter, per crop-technology pair.[25] In particular, we adjust $\delta_{\kappa\tau}$ according to: (1) aggregate production quantity of every crop k in the US, and (2) aggregate land share of modern technology in the USA, for every crop k.

To recover $a_{i,0}^f$, we use field-level data from EarthStat on the share of total cropland. Setting total cropland share from the model, $\alpha_{i,0}^f = \sum_k \alpha_{i,k}^f$, to that in EarthStat, $\alpha_{i,0}^{f,data}$, and using

[23]Specifically, in their cross-country estimates, they find income elasticity of agriculture to be around that of manufacturing minus one, and the substitution elasticity around half (see Table 3 in their paper).

[24]Here, $\widetilde{h}_{k\tau}$ can be thought of as an unobserved term implied by a vector of global prices implicit in the construction of the data on potential yields.

[25]Note that, in general, there are $T \times K \times F$ unobserved productivity shifters $\{a_{i,k\tau}^f\}$ with $T = 2$, $K = 10$, $F > 10^6$. Using potential yield data, we reduce this enormous number by several orders of magnitude down to only $T \times K$ unknown parameters $\{\delta_{k\tau}\}$.

equation (4), we recover field-level investment intensity parameters,

$$a_{i,0}^{f} = \frac{1}{P_i^0} \left(\sum_k (H_{i,k}^f)^{\theta_1} \right)^{\frac{1}{\theta_1}} \left(\frac{1-\alpha_{i,0}^{f,data}}{\alpha_{i,0}^{f,data}} \right)^{\frac{1}{\theta_1}}. \tag{28}$$

To calibrate factor shares, we impose the same factor shares across crops due to data limitations (i.e., $\gamma_{k\tau}^{L} = \gamma_{\tau}^{L}$, $\gamma_{k\tau}^{M} = \gamma_{\tau}^{M}$, $\gamma_{k\tau}^{N} = \gamma_{\tau}^{N}$ and $\gamma_{k}^{j,M} = \gamma^{j,M}$). We set the share of every input j ($\gamma^{j,M}$) according to USDA Commodity Costs and Returns, which gives $\gamma^{Fert,M} = 0.256$, $\gamma^{Pest,M} = 0.158$, and $\gamma^{Mach,M} = 0.585$. This leaves us with six technology-specific factor shares to measure. To this end, we use aggregate share of land, labor, and inputs in the US $\{\gamma_{USA}^{L,data}, \gamma_{USA}^{N,data}, \gamma_{USA}^{M,data}\}$. Each of these observed aggregate shares is an average between its corresponding traditional and modern factor shares. Following the definition given by FAO-GAEZ, we set input share of the traditional technology to zero, $\gamma_0^M = 0$. This together with $\gamma_{USA}^{M,data} = 0.58$ pins down γ_1^M. Labor shares are $\gamma_\tau^N = 1 - \gamma_\tau^L - \gamma_\tau^M$ due to constant returns to scale (at the level of plots), meaning that we only need to pin down technology-specific land shares, γ_τ^L. Since we observe $\gamma_{USA}^{L,data} = 0.21$, which is the weighted average of γ_0^L and γ_1^L, we are left with only one unknown. We define $\tilde{\gamma}^L \equiv \gamma_0^L/\gamma_1^L$ and leave this final parameter for the estimation.

In our calibration problem, we take aggregate expenditure on agriculture and nonagriculture as well as employment in nonagriculture in every country i as given (i.e., $E_i^0 = E_i^{0,data}$, $E_i^1 = E_i^{1,data}$,$N_i^0 = N_i^{0,data}$) and solve for prices $\{p_{n,g}\}$ such that equations (1)–(19) hold, productivity shifters satisfy (27)-(28), and factor shares are set as described above. We represent this inner problem as $c(\Gamma;\Theta) = 0$.

Estimation (Outer Problem). We construct four sets of statistics to jointly estimate $\Theta = \{\theta_1, \theta_2, \tilde{\gamma}^L\}$. These statistics are aggregate moments that summarize data variations in order to identify Θ. (In the next section we discuss about identification.) Our first set of statistics is based on cross-country variations in input cost share. Defining s_i as the cost share of inputs and N_q as the set of countries in the qth quartile of GDP per capita, we construct:

$$m_q^1 = \frac{1}{|N_q|} \sum_{i \in N_q} s_i, \quad q = 1,2,3,4 \qquad \text{(input cost share)}$$

Our second set of statistics is based on cross-country variations in fertilizer-per-land, v_i. To exploit the degree to which these measures vary across low and high income countries, we construct:

$$m_q^2 = \frac{1}{|N_q|} \sum_{i \in N_q} \log(v_i) - \frac{1}{|N_4|} \sum_{i \in N_4} \log(v_i), \quad q = 1,2,3 \qquad \text{(fertilizer-per-land)}$$

The above two sets of moments contain information about how measures of agricultural input-intensity vary across countries with different GDP per capita.

Our third set of statistics summarizes the relationship between input-intensity and land productivities (yields) across countries. Defining $x_{i,k} = (Q_{i,k}/L_{i,k}) / (\sum_i (Q_{i,k}/L_{i,k})/N)$, we call $x_i = L_{i,k}x_{i,k}/\sum_k L_{i,k}$ as the average normalized yield in country i (weighted by land shares). Figure A.1 shows that in the data, there is a positive, strong cross-country relationship between average normalized yield x_i and cost share of inputs, s_i. To exploit this empirical relationship, we define N_q^s as the set of countries in the qth quartile of cost share of inputs, and construct the following:

$$m_q^3 = \frac{1}{|N_q^s|}\sum_{i\in N_q^s}\log(x_i) - \frac{1}{|N_4^s|}\sum_{i\in N_4^s}\log(x_i), \quad q = 1,2,3 \qquad \text{(yields)}$$

Our fourth and last set of statistics summarizes cross-country information about crop choices. We base this set of statistics on the share of every crop k relative to a reference crop k_0, denoted by $\ell_{i,k} = L_{i,k}/L_{i,k_0}$. We choose corn as the reference crop since virtually all countries produce corn. For every crop k, we define N_q^{k0} as the set of countries in the qth quartile of potential yield of crop k relative to the reference crop based on country-level average traditional technology, and similarly we define the set N_q^{k1} of countries for crop k based on modern technology. Figure A.3 shows that in the data, the land share of every crop is systematically larger in countries where potential yield of that crop is larger (both based on traditional and for modern technologies). We therefore construct:

$$\begin{cases} m_q^{4,0} = \frac{1}{K}\sum_k \left[\sum_{i\in N_q^{k0}}\log(\ell_{i,k}) - \sum_{i\in N_4^{k0}}\log(\ell_{i,k})\right], \quad q=1,2,3 \qquad \text{(land shares, traditional)} \\ m_q^{4,1} = \frac{1}{K}\sum_k \left[\sum_{i\in N_q^{k1}}\log(\ell_{i,k}) - \sum_{i\in N_4^{k1}}\log(\ell_{i,k})\right], \quad q=1,2,3 \qquad \text{(land shares, modern)} \end{cases}$$

Finally, let $\mathbf{m} = [\{m_q^1\}, \{m_q^2\}, \{m_q^3\}, \{m_q^{4,0}, m_q^{4,1}\}]$ stack all the statistics, and define $g(\Theta) = [\mathbf{m}(\Theta) - \mathbf{m}^{data}]$. Based on $\mathbb{E}[g(\Theta)] = 0$, we seek $\widehat{\Theta}$ that achieves:

$$\widehat{\Theta} = \arg\min_{\Theta}\ g(\Theta)g(\Theta)' \quad \text{subject to} \quad c(\Gamma;\Theta) = 0,$$

where $c(\Gamma;\Theta) = 0$ is the inner calibration problem.

5.3 Identification

This section discusses the identification of $\Theta = (\theta_1, \theta_2, \tilde{\gamma}^L)$. While these parameters are jointly identified, we explain how each of them is more closely connected to a subset of moments.

Our first two sets of moments, which are based on cross-country variations in input cost

Table 2: Parameter Values

Parameter	Description	Source	Estimate
a. Demand-side (Ω_D)			
σ_g for $g \in \mathcal{K}$	Elasticity of subst between countries - crops	International trade flows of crops	5.76 (0.32)
σ_g for $g \in \mathcal{O}, \mathcal{J}$	Elasticity of subst between countries - other goods	Literature	4
κ	Elasticity of subst between crops	Country-level expenditure on crops	4.16 (0.49)
η, ε^0, ε^1	Elasticities of non-homothetic CES	Comin, Lashkari, and Mestieri (2015)	0.5, 1.5, 0.5
$b_{ni,g} d_{ni,g}^{1-\sigma_g}$	Demand shifters of goods	Residuals from gravity equations	-
b_n^0 , b_n^1	Demand shifters of sectors	Using sector-level expenditure shares	-
$A_{i,g}$	Productivity shifters of non-crop goods	Fixed effects from gravity equations	-
b. Supply-side (Ω_S)			
θ_1	Productivity dispersion between crops	Minimum Distance	1.79 (0.44)
θ_2	Productivity dispersion between technologies	Minimum Distance	3.21 (0.67)
$\tilde{\gamma}^L$	Land intensity of traditional to modern	Minimum Distance	3.03 (0.19)
$a_{i,k\tau}^f$	Crop-technology productivity shifter	Potential yields from FAO-GAEZ	-
$a_{i,0}^f$	Investment intensity parameter	Cropland share from EarthStat	-
$\gamma_{k\tau}^N, \gamma_{k\tau}^L, \gamma_k^M, \gamma_k^{j,M}$	Factor and input shares	Calibration using $\tilde{\gamma}^L$ and USDA data	-

Notes: This table presents sources and estimation methods used for the quantification of our general equilibrium model. Standard errors for the estimation of the demand-side parameters are clustered at the country of origin and good level. Standard errors for the estimation of the supply-side parameters are obtained using a parametric bootstrap procedure based on 25 simulated samples (see Appendix D.2).

share ($\mathbf{m}^1$) and fertilizer-per-land ($\mathbf{m}^2$), are informative about technology choices and key to the identification of $(\theta_2, \tilde{\gamma}^L)$. To clarify this point, using equations (1) and (3), we derive:

$$\ln\left(\frac{\alpha^f_{i,k1}}{\alpha^f_{i,k0}}\right) = \underbrace{\theta_2 \ln\left(\frac{a^f_{i,k1}}{a^f_{i,k0}}\right)}_{\text{Relative Productivities}} \underbrace{+\theta_2\left(\frac{\gamma^N_{k0}}{\gamma^L_{k0}} - \frac{\gamma^N_{k1}}{\gamma^L_{k1}}\right)\ln\left(\frac{w_i}{p_{i,k}}\right)}_{\text{Wages}} \underbrace{+\theta_2\left(-\frac{\gamma^M_{k1}}{\gamma^L_{k1}}\right)\ln\left(\frac{m_{i,k}}{p_{i,k}}\right)}_{\text{Input Prices}} \tag{29}$$

This expression shows that θ_2 controls the responses of relative land share of modern technology to relative productivity of modern technology ($a^f_{i,k1}/a^f_{i,k0}$), relative wage ($w_i/p_{i,k}$), and relative input price ($m_{i,k}/p_{i,k}$). When θ_2 is lower, all these components have a uniformly smaller effect on the relative use of modern technology. In contrast, when γ^L_0 is higher and γ^L_1 is lower (i.e. larger $\tilde{\gamma}^L$), these three components will have distinct effects on the use of modern technology: the effect of relative wage and relative input price increases, but that of relative productivity of modern technology remains unchanged. As such, θ_2 and $\tilde{\gamma}^L$ govern variations in the relative use of modern technology across fields, which is responsible for cross-country variations in input cost shares and input use per land. We capture the variations in these measures of input-intensity by our first two sets of moments: $\{m^1_q\}$ and $\{m^2_q\}$. Also, in Appendix D.1, we show that relative land share of modern technology, ($\alpha^f_{i,k1}/\alpha^f_{i,k0}$), is tightly mapped to input cost share ($\mathbf{m}^1$) and fertilizer-per-land ($\mathbf{m}^2$); and that, θ_2 and $\tilde{\gamma}^L$ play a key role in this mapping.

Our third set of moments, $\mathbf{m}^3$, reflects the extent to which land productivities are larger in countries where agricultural production is input-intensive. This relationship is particularly informative about $\tilde{\gamma}^L$. To provide intuition, we note that conditional on the producers' selections, the ratio of modern-to-traditional average land productivity in a field equals $\tilde{\gamma}^L \equiv \gamma^L_{k0}/\gamma^L_{k1}$ (see Appendix D.1). So, differences in land productivities (yields) between countries that tend to use traditional technologies more intensively and those that use modern technologies more intensively are informative about $\tilde{\gamma}^L$.

Our fourth set of moments, $\mathbf{m}^4$, contains information about crop choices, which is key to the identification of θ_1. Invoking equation 3, variations in returns to crops, captured by $a^f_{i,k\tau}$ and $h_{i,k\tau}$, induce smaller variations in crop-level land shares when θ_1 is lower. The identification of θ_1 exploits the relationship between variations in land shares of crops and variations in potential yields, controlling for the model-implied variations in $h_{i,k\tau}$.

5.4 Estimation Results

5.4.1 Estimated Parameters

Table 2 summarizes our estimation results. On the demand side, we have estimated the elasticity of substitution for crops across supplying countries, σ_k, at 5.76; and the elasticity of substitution across crops, κ, at 4.16. On the supply side, our estimation sets $\theta_1 = 1.79$, $\theta_2 = 3.21$, and

$\tilde{\gamma}^L = 3.03$.

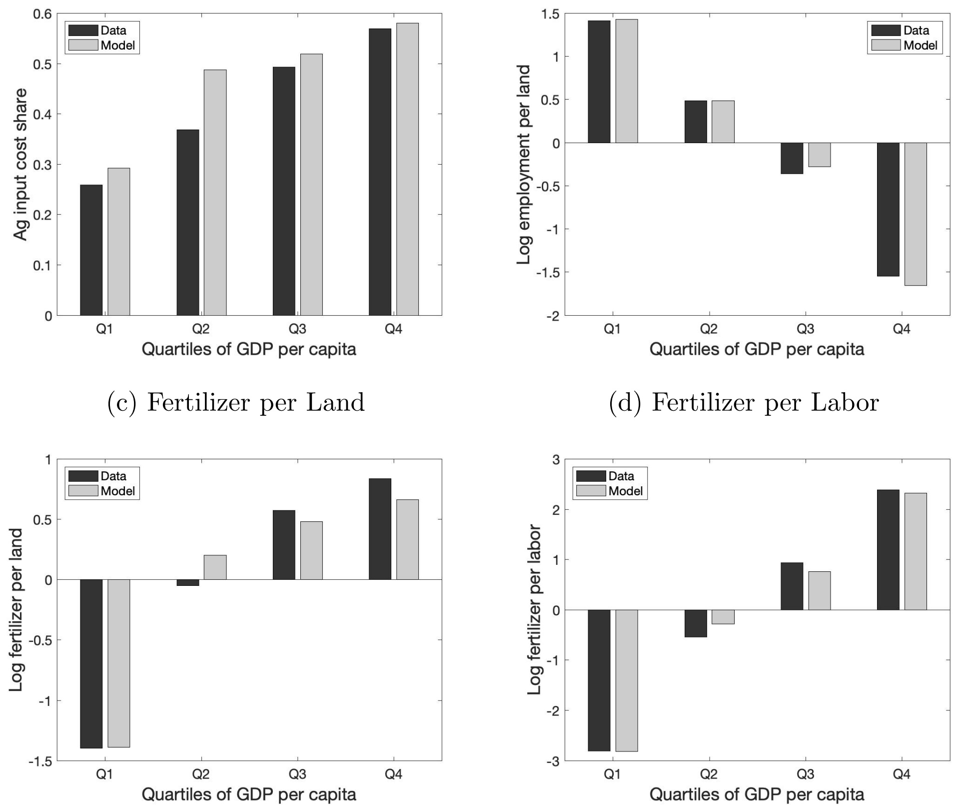
Figure 5: Model Fit –Moments of Input-Intensity

(a) Cost share of Agricultural Inputs

(b) Labor per Land

(c) Fertilizer per Land

(d) Fertilizer per Labor



Notes: This figure shows the model fit with respect to measures of agricultural input and labor intensity and GDP per capita across countries. The grey bars are predicted values from the model, and the black bars are their counterparts in the data. We normalize GDP per capita, fertilizer-per-land, labor-per-land, and fertilizer-per-labor according to their global averages.

Our estimate of θ_1 is in the range suggested by the literature. Using variations in crop outputs across countries, Costinot, Donaldson, and Smith (2016) estimate this elasticity at 2.6 and, using variations in land shares and prices across Peruvian regions, Sotelo (2020) estimate a value of 1.6. To the best of our knowledge, we are the first to estimate a technology-related elasticity, such as θ_2, so we do not have a benchmark for comparison. Our estimates imply that productivity draws between technologies within crops are more similar than productivity draws between crops. Accordingly, agricultural producers are more responsive in substituting between technologies within a choice of crop, than substituting between crops.[26]

To understand our estimate of $\tilde{\gamma}^L$, recall that the ratio of modern-to-traditional average land

[26]Notice that this does not necessarily imply that technology choices would change more than crop choices in comparative statics analyses of our model. We may observe large changes in crop choices with little changes in technology in a scenario where the change to wages and prices of inputs is small but the change to relative prices of crops is large.

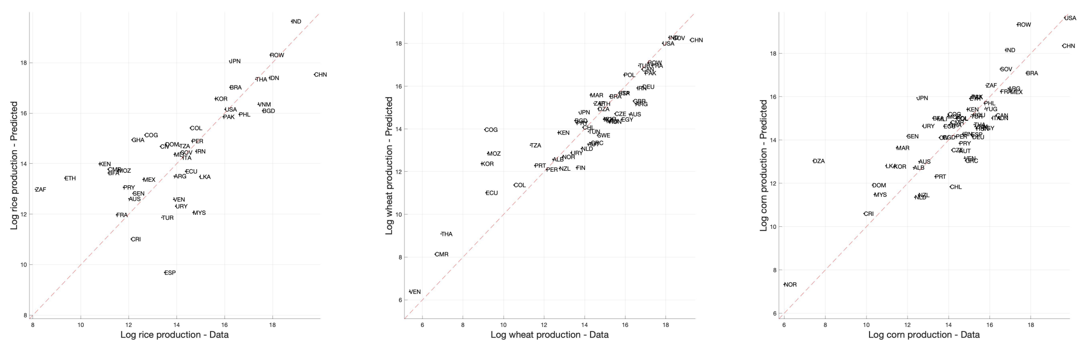
productivity, $\left(\frac{Q^f_{i,k1}}{L^f_{i,k1}}\right) \Big/ \left(\frac{Q^f_{i,k0}}{L^f_{i,k0}}\right)$, equals $\tilde{\gamma}^L$. This productivity ratio is *conditional* on the selection of crop-technology pairs that maximize returns to land. In comparison, the unconditional ratio of modern-to-traditional land productivity, $\tilde{\gamma}^L \left(\tilde{h}_{ik1} a^f_{ik1}\right) \Big/ \left(\tilde{h}_{ik0} a^f_{ik0}\right)$, is on average 9.52 across all crops and fields. This means that adjustments due to the selection margin bring down the unconditional ratio from 9.52 to 3.30 at the equilibrium.

5.4.2 Model Fit

In this section, we evaluate the fit of the model with respect to several dimensions of data that are critical for our analyses. We first highlight that, because we calibrate productivity shifters in our model based on the FAO-GAEZ data, our quantification approach contrasts with papers in the trade literature that use exact hat algebra to compute counterfactuals. Using hat algebra has the great benefit of allowing researchers to sidestep the need to calibrate productivity shifters to compute counterfactuals. Since this approach requires a model to perfectly fit production and trade flows in the baseline data, it leaves little room for evaluating the model fit.

Figure 6: Model Fit – Output Quantity of Selected Crops

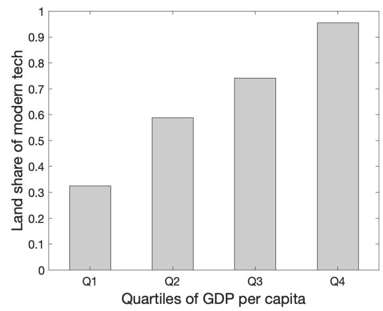
(a) Rice (b) Wheat (c) Corn



Notes: This figure shows the model fit with respect to output quantities across countries for the top three crops in terms of global revenues.

We start by inspecting the fit of our model with respect to crop-level variables on production, land use, and prices. Our model is calibrated to fit the aggregate output quantities of crops in the United States, but the predictions for other countries are entirely based on our estimated parameters and the variations in the potential yield data. Figure 6 depicts model predictions versus data for the three most important crops (in terms of their global production). In Appendix G.2.2, we report the model fit to output quantities of all crops, as well as the fit to land use of crops, and prices of crops. Overall, the model fits closely to the data on output quantities, land shares, and prices of crops across countries.

Figure 7: Model Predictions of Aggregate Land Share of Modern Technology



Notes: This figure shows model predictions of the aggregate share of land allocated to modern technology across countries in the quartiles of GDP per capita.

In addition, our model fits very well with respect to cross-country differences in agricultural input-intensity. Figure 5 reproduces the four plots of Empirical Pattern 1, together with model predictions, for every income quartile across countries. Our model replicates key relationships between economic development and input-intensity in agriculture. We emphasize that, if we were to assume a single Cobb-Douglas technology with the same factor and input share across all countries, our model would not generate any cross-country variation in the cost share of inputs. To allow for this possibility under a single-tier Cobb-Douglas production function, we would then need to allow for exogenous, country-specific differences in factor and input shares, but that would be equivalent to assuming that every country has access to a different production technology. In our model, countries have access to the same set of technologies, and cross-country differences in factor and input shares emerge endogenously from producers' *choice* of technologies.

5.4.3 Sources of Technology Choices

To close this section, we take advantage of our model, at the parameter estimates, to decompose sources of agricultural technology differences around the world. Figure 7 shows our model prediction for the distribution of the share of land employed in modern technology across countries by quartiles of GDP per capita. By construction, since we calibrate our model to match aggregate land share of modern technology in the US at 95%, we expect a similar land share of modern technology for countries in the fourth quartile of GDP per capita. Technology use in other quartiles, however, is a direct result of our estimation. Our results are intuitive: there are substantial differences in the use of modern agricultural technology across countries and such differences are strongly associated with the level of economic development.

To dissect variations that account for differences in technology choices around the world, we make use of expression (29). Using the model-generated data at our estimated parameters, we decompose sources of variations in technology choices using the Shapley decomposition. The results are reported in Table 3.[27] We first decompose the effect from *exogenous* productivity premium ("local productivity premium"), and the combined effect of *endogenous* wages and input prices ("local market condition"). Across all fields around the geography of the world, variations in "local productivity premium" and "local market condition" account respectively for 33% and 67% of the variations in technology use.[28] We then zoom into the components of local market conditions. Using equation (29),

$$\ln\left(\frac{\hat{\alpha}^f_{i,k1}}{\hat{\alpha}^f_{i,k0}}\right) = \theta_2\left(\frac{\gamma^N_{k0}}{\gamma^L_{k0}} - \frac{\gamma^N_{k1}}{\gamma^L_{k1}}\right)\ln\left(\frac{w_i}{p_{i,k}}\right) + \theta_2\left(-\frac{\gamma^M_{k1}}{\gamma^L_{k1}}\right)\ln\left(\frac{m_{i,k}}{p_{i,k}}\right), \tag{30}$$

where $\ln\hat{\alpha}_{i,k\tau} = \ln\left(\alpha^f_{i,k\tau}\right) - \theta_2\ln\left(a^f_{i,k\tau}\right)$ is productivity-adjusted land share of technology τ. Using equation (30), we find that variations in relative wage and relative input price account for respectively 45% and 55% of variations in the productivity-adjusted land share of modern to traditional technology.

Lastly, we zoom into the components of input price. We examine the contribution of foreign trade in spatial variations in input prices. Invoking equation (11), the price index of agricultural inputs for the production of crop k in country n can be expressed as:

$$\log m_{n,k} = \underbrace{\left(\sum_j \gamma_k^{M,j}\log\tilde{p}_{j,n}\right)}_{\text{Domestic}} + \frac{1}{\sigma-1}\underbrace{\left(\sum_j \gamma_k^{M,j}\log\lambda_{nn,j}\right)}_{\text{Foreign}} \tag{31}$$

where $\tilde{p}_{j,n} \equiv p_{j,n}b_{nn,j}^{1/(1-\sigma)}d_{nn,j}$ is the domestic producer price adjusted by domestic demand shifter. The first term captures the effect of domestic conditions of the market for inputs, and the second term is an openness index that summarizes the effect from having access to foreign inputs. Applying the Shapley decomposition to equation (31), we find that variations in the openness index explains 29% of variations in input prices across countries.

This exercise shows the extent to which variations in each of the above-mentioned variables account for variations in technology choice. This analysis provides statistical insight to the relationships in our model that give rise to spatial differences in the use of technologies. In the next section, we run counterfactual exercises to evaluate implications of trade and technology for agricultural productivity and welfare around the world.

[27]The Shapley decomposition in our context determines the contribution of each right-hand-side variable in a regression by measuring the overall increase in R^2 generated by the inclusion of each variable. See Shorrocks (2013) for details about this decomposition method.

[28]Our results in this section complement findings from Adamopoulos and Restuccia (2018). Specifically, combining an accounting framework with the FAO-GAEZ data, and assuming that the same technology is employed across countries, they find that differences in agro-ecological conditions account for a small share of cross-country differences in agricultural land productivity. Here, our model indicates that differences in agro-ecological conditions explain one-third of spatial variations in the land share of modern to traditional technology.

Table 3: Decomposing the Drivers of Technology Choice

a. Decomposing Technology Choice: Productivity vs Markets Factors	
Productivity	Markets Factors
$\log\left(\frac{a^f_{i,k1}}{a^f_{i,k0}}\right)$	$\log\left(\frac{w_i}{p_{i,k}}\right)$ and $\log\left(\frac{m_{i,k}}{p_{i,k}}\right)$
33%	67%
b. Decomposing Market Factors: Wages vs Input Prices	
Wages	Input Prices
$\log\left(\frac{w_i}{p_{i,k}}\right)$	$\log\left(\frac{m_{i,k}}{p_{i,k}}\right)$
45%	55%
c. Decomposing Input Prices: Domestic vs Foreign	
Domestic	Foreign
$\sum_j \gamma_k^{M,j} \log \tilde{p}_{j,n}$	$\sum_j \gamma_k^{M,j} \log \lambda_{nn,j}$
71%	29%

Notes: This table reports the contribution of different factors in generating variations in technology choice across fields using the Shapley decomposition. For each panel, we divide variables into two groups on which we implement the decomposition. Panel (a) decomposes technology choices into exogenous factors related to land productivity and endogenous factors related to market conditions. Panel (b) decomposes the market factors into the effects from wages and input prices. Panel (c) decomposes input prices ($m_{i,k}$) into domestic and foreign components.

6 Counterfactual Exercises

Having quantified the model, we now turn to evaluating the role of international trade for agricultural productivity, food consumption, and welfare across the world. We distinguish two broad ways that international trade plays a role. First, reductions in trade barriers can bring about a more efficient reallocation of resources through both input- and output-side of agricultural production. Second, given trade barriers, foreign productivity growth in the production of agricultural inputs can increase domestic agricultural productivity through international trade. We shed light on the importance of these two channels by two sets of counterfactual exercises.

Section 6.2 presents our first set of exercises, in which we study the effects on agricultural productivity around the world from the recent wave of globalization. Specifically, we simulate a counterfactual in which we set trade costs of both agricultural inputs and outputs to their levels in 1980, while keeping all other parameters unchanged, and compare the outcome to the baseline of 2007. Since we are interested in comparing the relative importance of input-side (via technology adoption) versus output-side mechanisms (via international specialization), we simulate two additional counterfactuals in which once we set only trade costs of agricultural inputs to their levels in 1980, and once we do so only for agricultural outputs.

In Section 6.2, we present our second set of exercises, in which we evaluate the gains from domestic versus foreign productivity growth in the agricultural input sector. We first simulate a counterfactual in which productivities of agricultural inputs are set to their levels of 1980, and compare the outcome to the baseline of 2007. We then simulate a series of counterfactuals in which we set productivities of agricultural inputs to the 1980 levels for each country, one at a time. These exercises allow us to explore the gains to every country from international productivity growth in the agricultural input sector that were attainable only through international trade, beyond productivity growth in the domestic economy.

In what follows, we present all results in terms of the counterfactual economy relative to the baseline. For example, a negative welfare change must be understood as the welfare loss of moving from the baseline of 2007 to a counterfactual in which some of the parameters are set based on their 1980 values.

6.1 Globalization in Agricultural Input and Agricultural Output

Measuring Changes to Trade Costs. We measure changes to trade costs between 1980 and 2007 based on a common approach in the trade literature that uses bilateral trade flow data (see Head and Mayer (2014) for details). We explain our procedure in Section E.1 of the Appendix. We find that changes in trade costs between 1980 and 2007 for agriculture outputs are comparable to those of agricultural inputs (Appendix Figure A.7). The average reduction of trade costs (weighted by trade flows of 2007) across countries is approximately 40% for both agricultural outputs and agricultural inputs. In addition, the extent of reductions in trade costs were quite heterogeneous across regions (Appendix Figure A.7).

Globalization in Both Agricultural Inputs and Outputs. We begin our analysis by evaluating the effects of setting trade costs in agricultural inputs and outputs at their 1980 level. Specifically, defining $\Delta_{ni,g}$ as the percentage change in trade cost $d_{ni,g}$ from 2007 to 1980, we compute counterfactual demand shifters as $b_{ni,g}(\Delta_{ni,g}d_{ni,g})^{(1-\sigma_g)}$, which we feed into the simulation of the model. Table 4 shows that, due to these changes in trade costs, the domestic share of expenditure on agricultural inputs and outputs would increase, respectively, by 19.1% and 8.5%. Additionally, the share of land allocated to modern technology would be 4.1% lower. With this shift to traditional technologies, at the global scale, yields would be 7.6% lower on average, and share of labor employed in agriculture would be 6.3% higher. As a consequence of these changes in agricultural production across the world geography, global food consumption would fall by 3.7% and welfare would decrease by 2.4%.

Table A.2 in the appendix reports our results for countries in the quartiles of GDP per capita. The effects on agricultural productivity are more pronounced in the second and third quartiles. These middle-income countries tend to trade a larger share of their agricultural outputs, and rely more on modern agriculture which is intensive in the use of internationally-supplied inputs. However, the effects on welfare are larger for countries in the first quartile of GDP per capita. This occurs because poorer countries have a substantially larger share of expenditure on agricultural goods. In these countries, even small changes in food consumption translate into substantial welfare effects.

Table 4: Impact of Changes in Trade Costs from the Baseline in 2007 to the Counterfactual Economy in 1980 (Percentage change)

	Changes in Trade Costs in Agriculture		
	Output and Input	Only Input	Only Output
	(1)	(2)	(3)
a. Domestic expenditure shares			
Agricultural input	19.1	20.8	-2.8
Agricultural output	8.5	-1.3	9.8
b. Agricultural production			
Share of land in modern	-4.1	-4.9	0.9
Yield (avg across crops)	-7.6	-6.5	-0.8
Agricultural labor share	6.3	4.5	1.4
c. Welfare			
Food consumption	-3.7	-2.3	-1.4
Welfare	-2.4	-1.0	-1.3
d. Inequality (Q4/Q1)			
Food consumption	-2.8	-1.0	-1.7
Welfare	2.2	0.3	1.7

Notes: This table reports a summary of results for the counterfactuals in which we change trade costs to their levels in 1980. The table reports percentage changes of listed variable in the counterfactual with trade costs of agricultural inputs and/or agricultural outputs in 1980 relative to the baseline equilibrium of 2007.

The bottom panel of Table 4 reports the extent to which globalization in agricultural inputs and outputs affects inequality between countries. Welfare inequality, as measured by the 4th to 1st quartile ratio, increases by 2.2% in the counterfactual equilibrium. Because low-income countries spend a larger share of their budget on food, the global loss of efficiency in agricultural markets disproportionately hurts them, even though the effects on food consumption are significantly larger for richer countries (see Table A.2 in the appendix for detailed results). Next, we turn from the combined impact of changes in trade costs of agricultural inputs and outputs to examining their individual effects.

Globalization Only in Agricultural Inputs & Only in Agricultural Outputs Column (2) and (3) of Table 4 present, separately, the impact of reductions in trade costs of only agricultural inputs and only agricultural outputs. Overall, changes to yields, land share of modern technology, and agricultural labor share are substantially larger in the case of trade cost reductions in agricultural inputs (relative to agricultural outputs). It is also interesting that in the counterfactual related to inputs, domestic expenditure share (DES) of outputs slightly falls. This means that countries can produce more food for domestic consumption by having a better access to internationally-supplied inputs. The opposite is also true. In the counterfactual related to outputs, DES of agricultural inputs slightly decreases. This is because, at the margin, countries can import crops in which they do not have a comparative advantage instead of increasing domestic production of those crops using more inputs. As such, the input-side and output-side mechanisms act slightly against each other.

The global welfare loss is 1.0% in the case of only inputs, and 1.3% in the case of only outputs. In addition, the associated reduction in food consumption is 2.3% in the case of inputs, compared to 1.4% in the case of outputs. We thus find that the effects of globalization on welfare and food consumption via the input side of agriculture are as important as the output side.

We also highlight that the effects from input side operate through distinct channels (relative to output-side mechanisms). Panel (b) shows that yields are on average 6.5% lower across crops in the input-only counterfactual. This sizable loss of yields is associated with 20.8% increase in DES of agricultural inputs, 4.9% drop in the land share allocated to modern technology, and 4.5% increase in agricultural labor share. These results echo our theoretical analysis in Section 4.2. Due to larger trade barriers in the counterfactual, agricultural inputs are relatively more expensive, hence agricultural producers rely more on traditional technologies that have lower yields and use labor more intensively.

In addition, reductions in trade costs of agricultural inputs, compared to outputs, have substantially different distributional implications. The welfare loss generated by raising trade costs of agricultural outputs to their levels of 1980 is the largest for low-income countries—at -2.5% for countries in the bottom quartile of GDP per capita—and the smallest for high-income countries—at -0.8% for countries in the upper quartile of GDP per capita—. This result is largely driven by the fact that countries have larger share of expenditure on food at lower levels of income. The welfare loss generated by raising trade costs of agricultural inputs to their levels of 1980, however, is the largest for the middle-income countries—at -1.3 and -1.6% in the second and third quartiles of GDP per capita, respectively—. Two mechanisms drive these results. First, increases in the trade costs of agricultural inputs have a larger impact on the production costs of middle-income countries relative to low-income ones, since low-income countries have a notably smaller share of their land under modern agriculture. Second, in moving back to the counterfactual, middle-income countries compared to high-income countries experience larger drops in the use of modern technologies: 5.7% for the second quartile of the GDP per capita and 10.3 for the third quartile, while in high-income countries, use of modern technology falls by only 0.4%. The resulting effect on welfare then features an inverse-U shape along countries' level of economic development.[29] See Table A.2 for details.

[29]We check the extent to which heterogeneous changes to trade costs are responsible for these distributional outcomes, and confirm that they do not alter the main takeaway. Specifically, we repeat our exercises for the case where changes to trade costs are the same across countries and also between inputs and outputs (See Tables A.3 and A.4 in the appendix). A main finding is that the welfare effect of globalization in agricultural outputs

6.2 Gains from Domestic and International Growth in Productivity of Agricultural Inputs

Measuring Changes to Productivity of Agricultural Inputs. We measure changes to productivity of agricultural machinery and pesticides $\{A_{n,mach}, A_{n,pest}\}$, and production of fertilizers $\{V_n\}$, for every country between 1980 and 2007. Our measures of productivity of agricultural machinery and pesticides are based on the fixed effects recovered from gravity-type equations for exports of manufacturing. Section E.2 in the Appendix describes this procedure in details. For fertilizers, we calculate changes to production of fertilizers based on data from FAO-STAT. The growth in productivity of agricultural inputs between 1980 and 2007 are large: productivity of agricultural machinery and pesticides, averaged across countries, increased by approximately 126%; for fertilizers, global production increased by 55%.[30]

Impact of Productivity Changes in the Agricultural Input Sector. We consider two sets of counterfactuals, which in total contain $1 + N$ counterfactual exercises. In the first counterfactual, which we label as "shocks to all countries", we re-calibrate $\{A_{n,mach}, A_{n,pest}, V_n\}_{n=1}^{N}$ to their values in 1980 for all countries. In the next N counterfactuals, we re-calibrate $\{A_{n,mach}, A_{n,pest}, V_n\}$ to their values in 1980, for each country n, one at a time, amounting to N independent outcomes. In each of these N counterfactuals, we focus on the outcome of the country whose productivity parameters are re-calibrated. We refer to these counterfactual outcomes as "shocks, country by country".

Figure 8 summarizes our main results. To spell out the figure, consider the example of Colombia. Panel (a) shows that, in the shocks to all countries, welfare in Colombia would drop by 10.1%, but if the productivity shock was only to the Colombian agricultural input sector, its welfare would fall by 5.4%. Hence, 53 percent (= 5.4/10.1) of the welfare loss in Colombia can be attributed to its domestic productivity shock, and the remaining 47 percent can be attributed to foreign productivity shocks. By the same token, across countries, weighted by population, 39 percent of the welfare loss can be attributed to foreign productivity shocks. In our exercise with "shocks to all countries", welfare falls by 15.3% at the global level. Attributing 39 percent of this welfare loss to the international transmission of productivity shocks, we get a welfare loss of 5.95%, which is 2.5 times larger than the welfare loss of setting trade costs of agricultural inputs and outputs back to their levels in 1980. Hence, the indirect welfare effect of trade associated with the transmission of productivity shocks across countries were larger than the direct effect of trade generated by reductions in trade costs. Another important takeaway

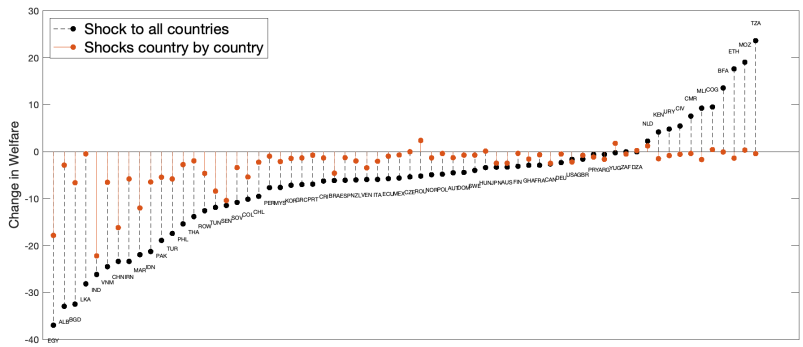
remains to be decreasing from the 4th to 1st quartile of GDP per capita, while the welfare effect of globalization in agricultural inputs remains to feature an inverse-U shape.

[30]The heterogeneity in productivity growth across regions is substantial, as shown in Figure A.8. For example, productivity of machinery and pesticides rose by 700% in East Asia and by 200% in the Middle East or Latin America. Production of fertilizers grew substantially across Asian countries while it slightly declined in Europe.

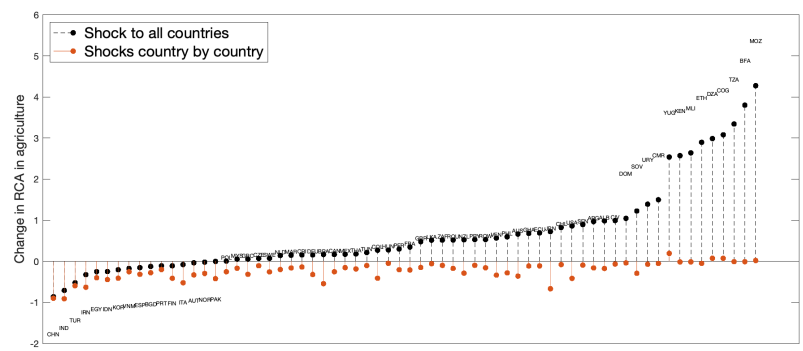
is that the benefits from foreign productivity shocks to the agricultural input sector, realized through across to internationally-supplied inputs, were overall comparable with the benefits from domestic productivity shocks.

Figure 8: Impact of Changes in Productivity of Agricultural Inputs

(a) Welfare



(b) Revealed Comparative Advantage in Agriculture



Notes: These figures report results for (i) 66 counterfactuals in which we re-calibrate the productivity of agricultural inputs country by country, one at a time, and (ii) one counterfactual in which we re-calibrate the productivity of agricultural inputs in all countries at once. The red dots represent the outcome for the country whose productivity parameters are re-calibrated in the case of (i), and the black dots represent the outcome in the case of (ii). Panel (a) reports the percentage change to welfare. Panel (b) reports the Balassa index of revealed comparative advantage in agriculture, $RCA_i = (EXP_{i1}/EXP_{i0}) / (\sum EXP_{i1} / \sum EXP_{i0})$, where EXP_{i1} denotes exports of country i in agriculture and EXP_{i0} that of non-agriculture.

Our results reveal that the effects of the global change in the productivity of agricultural inputs are massively heterogeneous across countries: while middle-income and high-income countries that already had a substantial share of their land employed in modern technologies tend to benefit from these global productivity changes, low-income countries with larger scope for increasing their use of modern technologies tend to benefit very modestly, and in fact, often lose. To help explain this interesting result, which might seem counter-intuitive at first glance, we depict the percentage change to the Balassa index of revealed comparative advantage (RCA) in Panel (b) of Figure 8. The RCA index captures the degree to which a country's exports concentrates in agriculture (relative to non-agriculture) compared to an average country in the world. Panel (b) shows that a move from the baseline to the counterfactual economy generates a large increase in the agricultural RCA of low-income countries, but a small increase or decrease in that of other countries. This occurs because in the counterfactual economy low-income countries become more competitive in exporting agricultural goods in international markets relative to other countries. Since a large proportion of total exports in these countries comes from agricultural exports, the improvement in their competitiveness through agricultural exports translates into substantially higher welfare in the counterfactual.[31]

Lastly, our results show that domestic productivity growth in the production of agricultural inputs incentivizes the use of modern, input-intensive technologies and reallocates labor out of agriculture. In the spirit of classic studies in economic development such as Schultz et al. (1968), this mechanism can be interpreted as a "domestic push force". In addition, our results indicate that "push forces" spurs also from foreign sources. Comparing the effects of the "shocks, country by country" counterfactuals to "shocks to all countries" one, we find that the effects of foreign productivity growth in the production of agricultural inputs are key: Global agricultural employment is 4.8 percentage points higher when all countries in the world experience productivity growth, and 0.8 percentage points higher when we sum the effects to each individual country when they experience only their own productivity growth. Borrowing the language in economic development, we consider this second type of shock as an "international push force".[32]

7 Conclusion

We studied the impact of international trade in agricultural inputs on the adoption of modern, input-intensive agricultural technologies, and implications for agricultural productivity and welfare around the world. To this end, we developed a new quantifiable, multi-country general equilibrium model that incorporates two margins of productivity gains from trade: one related to crop specialization, another to technology adoption. We brought our model to extremely rich measures of agricultural productivity from FAO-GAEZ covering about 1.1 million fields across the world. We conducted two sets of counterfactual exercises to gauge the effects of trade on technology adoption: one in which we examine the impact of the large reductions in trade costs between 1980 and 2007, another in which we study the benefits from the international transmission of productivity growth in the agricultural input sector during this same period.

[31]Figure A.1 in the Appendix shows that low income countries tend to have a substantially larger portion of their export earnings coming from agriculture.

[32]Consistent with the hypothesis that improvements in agricultural technology prevents the expansion of cropland, which has been termed as the "Borlaug hypothesis", we find that the use of land in agriculture rises as we move from the baseline economy to the counterfactuals with input productivities of 1980. Gollin, Hansen, and Wingender (2018) also find support for the "Borlaug hypothesis", exploiting variations in the timing of the Green Evolution across countries.

Our results deliver a few important, yet unexplored, welfare implications. First, trade in agricultural inputs, through the novel channel of technology adoption, was as important as trade in agricultural outputs, through the traditional channel of international crop specialization. Therefore, in evaluating the welfare implications of agricultural globalization, one would miss much by ignoring the interplay between input use and technology adoption. In addition, there are nontrivial distributional effects of globalization in agricultural inputs across countries. Reductions in trade costs of agricultural inputs widened the productivity gap between low-income and middle-income countries, while compressing the gap between middle-income and high-income countries. Lastly, the indirect welfare effects of trade, related to the transmission of the the benefits of growth in the productivity of agricultural inputs across country borders, were remarkably large at the global scale, although not particularly large for low-income countries.

We offer tools and insights that can be applied in several areas of research beyond the scope of this paper. First, the key mechanism explored here—the interaction between trade in intermediates and mechanization of production—also operates in non-agriculture sectors. For example, in the past two decades, labor employment in manufacturing sharply declined in high-income countries, while rising in some middle- and low-income countries. We believe that our understanding of this phenomenon can be improved by taking into account interactions between technology choices and trade in intermediate inputs. Second, our study paves down the road to explore other aspects of agricultural modernization, such as its implications to inter-regional migration, dynamics of structural transformation, and carbon emissions. Finally, high-resolution datasets are increasingly becoming available at the intersections of natural and social sciences. We take a step forward in incorporating such data into a theoretical framework that can be used for a wide range of applications. Integrating these types of micro-level data into economic models appears as a promising direction for future research, particularly with applications to resources and environment.

References

Adamopoulos, T., and D. Restuccia (2018): "Geography and agricultural productivity: Cross-country evidence from micro plot-level data," Discussion paper, National Bureau of Economic Research.

Allen, T., and D. Donaldson (2020): "Persistence and Path Dependence in the Spatial Economy," *Unpublished manuscript.*

Alvarez-Cuadrado, F., and M. Poschke (2011): "Structural change out of agriculture: Labor push versus labor pull," *American Economic Journal: Macroeconomics*, 3(3), 127–58.

Antras, P., T. C. Fort, and F. Tintelnot (2017): "The margins of global sourcing: Theory and evidence from us firms," *American Economic Review*, 107(9), 2514–64.

Arkolakis, C., A. Costinot, and A. Rodriguez-Clare (2012): "New trade models, same old gains," *American Economic Review*, 102(1), 94–130.

Bergquist, L. F., B. Faber, T. Fally, M. Hoelzlein, E. Miguel, and A. Rodriguez-Clare (2019): "Scaling Agricultural Policy Interventions: Theory and Evidence from Uganda," *Working Paper.*

Bustos, P. (2011): "Trade liberalization, exports, and technology upgrading: Evidence on the impact of MERCOSUR on Argentinian firms," *American economic review*, 101(1), 304–40.

Bustos, P., B. Caprettini, and J. Ponticelli (2016): "Agricultural productivity and structural transformation: Evidence from Brazil," *American Economic Review*, 106(6), 1320–65.

Caliendo, L., and F. Parro (2015): "Estimates of the trade and welfare effects of NAFTA," *Review of Economic Studies*, 82(1), 1–44.

Caselli, F. (2005): "Accounting for cross-country income differences," *Handbook of economic growth*, 1, 679–741.

Comin, D. A., D. Lashkari, and M. Mestieri (2015): "Structural change with long-run income and price effects," Discussion paper, National Bureau of Economic Research.

Costinot, A., D. Donaldson, and C. Smith (2016): "Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world," *Journal of Political Economy*, 124(1), 205–248.

Costinot, A., and A. Rodríguez-Clare (2014): "Trade theory with numbers: Quantifying the consequences of globalization," in *Handbook of international economics*, vol. 4, pp. 197–261. Elsevier.

Donovan, K. (2017): "Agricultural risk, intermediate inputs, and cross-country productivity differences," *Working Paper.*

Eaton, J., and S. Kortum (2002): "Technology, geography, and trade," *Econometrica*, 70(5), 1741–1779.

Eaton, J., S. Kortum, and F. Kramarz (2011): "An anatomy of international trade: Evidence from French firms," *Econometrica*, 79(5), 1453–1498.

Fajgelbaum, P., and S. J. Redding (2019): "External integration, structural transformation and economic development: Evidence from argentina 1870-1914," Discussion paper, Working Paper.

Farrokhi, F. (2020): "Global sourcing in oil markets," *Journal of International Economics*, p. 103323.

Farrokhi, F., and A. Soderbery (2020): "Trade Elasticities in General Equilibrium," .

Feenstra, R. C., R. E. Lipsey, H. Deng, A. C. Ma, and H. Mo (2005): "World trade flows: 1962-2000," Discussion paper, National Bureau of Economic Research.

Fieler, A. C., M. Eslava, and D. Y. Xu (2018): "Trade, quality upgrading, and input linkages: Theory and evidence from colombia," *American Economic Review*, 108(1), 109–46.

Fuglie, K. (2012): "Productivity Growth and Technology Capital in the Global Agricultural Economy," *Productivity growth in agriculture: An international perspective*, p. 335.

Galle, S., A. Rodríguez-Clare, and M. Yi (2017): "Slicing the pie: Quantifying the aggregate and distributional effects of trade," Discussion paper, National Bureau of Economic Research.

Goldberg, P. K., A. K. Khandelwal, N. Pavcnik, and P. Topalova (2010): "Imported intermediate inputs and domestic product growth: Evidence from India," *The Quarterly journal of economics*, 125(4), 1727–1767.

Gollin, D., C. W. Hansen, and A. Wingender (2018): "Two Blades of Grass: The Impact of the Green Revolution," Working Paper 24744, National Bureau of Economic Research.

Gollin, D., S. L. Parente, and R. Rogerson (2007): "The food problem and the evolution of international income levels," *Journal of Monetary Economics*, 54(4), 1230–1255.

Gouel, C., and D. Laborde (2018): "The crucial role of international trade in adaptation to climate change," Discussion paper, National Bureau of Economic Research.

Griliches, Z. (1958): "The demand for fertilizer: An economic interpretation of a technical change," *Journal of Farm Economics*, 40(3), 591–606.

Head, K., and T. Mayer (2014): "Gravity equations: Workhorse, toolkit, and cookbook," in *Handbook of international economics*, vol. 4, pp. 131–195. Elsevier.

Hertel, T. W. (2002): "Applied general equilibrium analysis of agricultural and resource policies," *Handbook of agricultural economics*, 2, 1373–1419.

Horowitz, J. L. (2001): "The bootstrap," in *Handbook of econometrics*, vol. 5, pp. 3159–3228. Elsevier.

Imbs, J., and I. Mejean (2015): "Elasticity optimism," *American Economic Journal: Macroeconomics*, 7(3), 43–83.

Inklaar, R., and M. P. Timmer (2008): "GGDC productivity level database: International comparisons of output, inputs and productivity at the industry level.," *Groningen Growth and Development Centre Research Memorandum GD-104*.

Johnson, W., and M. Fiszbein (2020): "Labor Push versus Comparative Advantage: Agricultural Productivity, Openness, and Structural Change," *Working Paper*.

Johnston, B. F., and J. W. Mellor (1961): "The role of agriculture in economic development," *The American Economic Review*, 51(4), 566–593.

Kucheryavyy, K., G. Lyn, and A. Rodríguez-Clare (2016): "Grounded by gravity: A well-behaved trade model with industry-level economies of scale," Discussion paper, National Bureau of Economic Research.

Lashkaripour, A., and V. Lugovskyy (2018): "Scale economies and the structure of trade and industrial policy," *Working Paper*.

Lee, D. R., and P. G. Helmberger (1985): "Estimating supply response in the presence of farm programs," *American Journal of Agricultural Economics*, 67(2), 193–203.

Lind, N., and N. Ramondo (2018): "Trade with correlation," Discussion paper, National Bureau of Economic Research.

Matsuyama, K. (1992): "Agricultural productivity, comparative advantage, and economic growth," *Journal of Economic Theory*, 58(2), 317 – 334.

McArthur, J. W., and G. C. McCord (2017): "Fertilizing growth: Agricultural inputs and their effects in economic development," *Journal of development economics*, 127, 133–152.

McFadden, D. (1981): "Econometric models of probabilistic choice," *Structural analysis of discrete data with econometric applications*, 198272.

Nurkse, R. (1953): *Problems of capital formation in underveloped countries*. Oxford University Press.

Pellegrina, H. S. (2020): "Trade, Productivity and the Spatial Organization of Agriculture: Evidence from Brazil ," *Working Paper*.

Porteous, O. (2020): "Trade and agricultural technology adoption: Evidence from Africa," *Journal of Development Economics*, p. 102440.

Ramondo, N., and A. Rodríguez-Clare (2013): "Trade, multinational production, and the gains from openness," *Journal of Political Economy*, 121(2), 273–322.

Restuccia, D., D. T. Yang, and X. Zhu (2008a): "Agriculture and aggregate productivity: A quantitative cross-country analysis," *Journal of Monetary Economics*, 55(2), 234 – 250.

——— (2008b): "Agriculture and aggregate productivity: A quantitative cross-country analysis," *Journal of monetary economics*, 55(2), 234–250.

Rostow, W. W., and W. W. Rostow (1990): *The stages of economic growth: A non-communist manifesto*. Cambridge university press.

Schultz, T. W., et al. (1968): "Economic growth and agriculture.," *Economic growth and agriculture.*

Shorrocks, A. F. (2013): "Decomposition procedures for distributional analysis: a unified framework based on the Shapley value," *The Journal of Economic Inequality*, 11(1), 99–126.

Simonovska, I., and M. E. Waugh (2014): "The elasticity of trade: Estimates and evidence," *Journal of international Economics*, 92(1), 34–50.

Sotelo, S. (2020): "Domestic Trade Frictions and Agriculture," *Forthcoming in Journal of Political Economy.*

Taheripour, F., X. Zhao, M. Horridge, F. Farrokhi, and W. Tyner (2020): "Land Use in Computable General Equilibrium Models," *Journal of Global Economic Analysis*, 5(2), 63–109.

Teignier, M. (2018): "The role of trade in structural transformation," *Journal of Development Economics*, 130, 45–65.

Tombe, T. (2015): "The Missing Food Problem: Trade, Agriculture, and International Productivity Differences," *American Economic Journal: Macroeconomics*, 7(3), 226–258.

Yeaple, S. R. (2005): "A simple model of firm heterogeneity, international trade, and wages," *Journal of international Economics*, 65(1), 1–20.

Online Appendix for "Trade, Technology and Agriculture Productivity"

Farid Farrokhi and Heitor S. Pellegrina

A Data

This section describes in detail the datasets used in our paper. First, we present the data on potential yields coming from FAO-GAEZ. Second, we describe the data on cropland from EarthStat. Third, we explain how we construct our data on trade and production, which combines information from CEPII, OECD, STAN, FAO, and UNIDO. Lastly, we describe our construction of the data on consumption shares and labor shares in agriculture, which uses data from the World Bank, Eurostat, and UN-ILO.

Potential Yields. The data on potential yields (also called "maximum attainable yields") comes from Global Agro-Ecological Zones (GAEZ) project, which is produced by the International Institute for Applied System Analysis (IIASA) and the Food and Organization of the United Nations (FAO). The data is measured at the field level, which is often called in the literature as grid cells or agro-ecological zones. Fields represent an area of 5 min by 5 min, which encompasses an area of approximately 10 by 10 km. Among the different measures produced by FAO-GAEZ, we use for our analysis data on agro-climatically attainable biomass by crop and specific land utilization types (LUTs). The different types of land utilization corresponds to what we denote by different technologies in our model. The estimation of the maximum attainable yield is based on a function that maps rich climate data into maximum attainable yields. The variables in the climate data include, among others, the dominant type of soil, altitude, slope, temperature, frost-free period during a year, and annual precipitation. In addition, the data is available for climates in different reference periods. We pick the one that is based on the 1961-1990 period. The parameters of this function depend on each LUT and crop. Local socio-economic conditions do not enter as an input in the estimation of maximum attainable yields. As such, variations in maximum attainable yields across fields reflect differences in agro-ecological conditions and not differences in the level of economic development of a field. Indeed, we find little to no systematic variation between maximum attainable yields and gdp per capita in our data once we control for a parsimonious set of geographic characteristics of a field.

In FAO-GAEZ, the land utilization types that define technologies in agricultural production are divided into three groups. First, there is a low level of input use type, which corresponds to a farming system that is largely subsistence based. This dataset represents the maximum attainable yield if farmers use traditional cultivars and, importantly, no application of nutrients, no use of chemicals and minimum conservation measures. Therefore, we denote this technology as traditional in our analysis. Second, there is an intermediate level of input use type, which corresponds to a farming system that is partly market oriented. We do not directly use this type of technology because we do not have enough data to identify an additional set of parameters for factor- and input-intensity in our model. Third, the high level of input use type, which corresponds to a modern farming system. In this case, production is fully mechanized and uses optimum applications of nutrients and chemical pest, disease and weed control.

Cropland. The data on the share of total cropland in every field comes from EarthStat. The grid cells defined by EarthStat are the same as the ones in FAO-GAEZ, a feature that greatly facilitates merging the data from these two sources. The project is a collaboration between the Global Landscapes Initiative at the University of Minnesota's Institute on the Environment and the Land Use and Global Environment Lab at the University of British Columbia. Among the several datasets organized by EarthStat, we use information on the share of total cropland. The construction of this dataset is based on two satellite imagery datasets circa 2000, Boston University's Moderate resolution Imaging Spectrometer (MODIS) and the Satellite Pour l'Observation de la Terre (SPOT) VEGETATION based on Global Land Cover 2000 (GC2000), and agricultural inventory data. The agricultural inventory data is used to train a land cover classification that takes the satellite imagery as an input. In particular, the inventory data set combines demographic censuses, agricultural censuses and national level statistics from FAO-STAT.

Trade and Gross Output. Our data set on gross output and bilateral trade flows is constructed based on the year of 2007, which serves as the baseline year throughout our paper, and include the following sectoral groups: non-agriculture, agriculture (not disaggregated by crops), agricultural inputs (disaggregated by fertilizers, machinery and pesticide), and crops. We next explain the procedures that we apply for the construction of the data for each of these sectoral groups.

For the non-agriculture sector, we first bring bilateral trade flow data from BACI-CEPII. We then construct gross output using domestic expenditure shares ($\lambda_{ii,0}$) as follows. We collect data on domestic expenditure shares ($\lambda_{ii,0}$) from the World-Input Output Database (WIOD), CEPII, and Input-Output tables from OECD. For the countries without direct data on domestic trade shares, we bring UNIDO data on gross output with sectoral disaggregation at the 2 digit level, which allows us to separate agriculture from non-agriculture, and construct domestic expenditure shares ($\lambda_{ii,0}$) using $\lambda_{ii,0} = (Y_{i,0}^{data} - X_{i,0}^{data})/(Y_{i,0}^{data} - X_{i,0}^{data} + M_{i,0}^{data})$, where $Y_{i,0}^{data}$ is the gross output, $X_{i,0}^{data}$ is non-agriculture exports, and $M_{i,0}^{data}$ is non-agriculture imports. Finally, with our measures of domestic trade shares, we construct implied gross output using $Y_{i,0} = X_{i,0}^{data} + M_{i,0}^{data}\lambda_{ii,0}/(1-\lambda_{ii,0})$. For the agricultural sector as a whole, we follow a very similar procedure. We also use bilateral trade flow data from BACI-CEPII, but we instead bring in gross-output data from STAN and FAO-STAT to construct $\lambda_{ii,1}$ when domestic expenditure shares are not directly available.

For each category of agricultural input (fertilizers, pesticides and agricultural machinery), we construct our bilateral trade flow data using BACI-CEPII. Here, we emphasize that our categories of fertilizers, pesticides, and agricultural machinery are aggregation over HS-6 digit products that are associated with any of these individual agricultural input categories. To identify these HS-codes, we closely follow the specifications used in FAO-STAT for the construction of trade data by agricultural inputs. We next turn to the construction of gross-output for each agricultural input category.

To measure gross-output for agricultural machinery, we first bring data on domestic expenditure shares of agricultural machinery using UNIDO data disaggregated at the 4 digit level data, which allows us to measure domestic expenditure share of agricultural machinery. When data was not available for a country, we used information on the domestic trade shares of general machinery. If data on the domestic trade shares of general machinery were not available, we applied the following procedure. We construct the log of the hazard ratio of domestic trade share in manufacturing ($\log(\lambda_{ii,0}/(1-\lambda_{ii,0}))$) , the log of the hazard ratio in domestic share of trade in non-agriculture ($\log(\lambda_{ii,0}/(1-\lambda_{ii,0})$) and run a regression of the latter against the former adding the size of the log of the gross output in manufacturing. By targeting the log of the hazard ratios, we ensure that the predicted values from our regressions are bounded between 0 and 1. The correlation between the predicted trade shares and the actual ones is 0.82. Using the predicted values from this regression, we construct the domestic share of trade in agricultural machinery for the remaining countries without data. For gross-output in pesticide, we apply the same procedure, but, for fertilizers, since we have data on quantities, we adopt a slightly different method.

To construct our data on gross-output for fertilizers, we take advantage of the availability of data on exports, production, consumption and imports of tonnes of fertilizer per nutrient from FAO-STAT with our data on trade flows in values. The data on fertilizers from FAO-STAT comes disaggregated according to three nutrients, i.e., nitrogen N, phosphate P and potassium K, which form the basis of chemical fertilizers (NPK). For simplicity, we summed the weight of the total amount of nutrients. Using the data from FAO-STAT, we construct the domestic share of consumption by dividing imports in quantity by total consumption in quantity. Using this domestic share of consumption ($\lambda_{ii,F}^{Q}$), we construct gross output in values using $Y_{i,F} = X_{i,F}^{data} + M_{i,F}^{data}\lambda_{ii,F}^{Q}/(1-\lambda_{ii,F}^{Q})$. Here, we rely on the assumption that domestic shares of consumption in quantity are equivalent to domestic share of consumption in values. This is the case when the price of imported fertilizers are on average the same as the price of fertilizers consumed from domestic source. This assumption is consistent with the Eaton and Kortum (2002) framework, where the average price of goods in a destination coming from any source is the same. Given our information on quantities, we measured the unit value of fertilizers by dividing exports of a country to itself with data on the corresponding quantities.

To construct our gross output and bilateral flow data by crop, we bring in data from FAO-STAT. The bilateral trade flow data available in FAO-STAT is constructed based on COMTRADE (as is BACI-CEPII), which is the official international trade data coming from the United Nations. The main benefit of FAO-STAT is that it already comes organized by crop. We therefore have to make minimal adjustments to crop names to ensure consistency between the trade and production data from FAO-STAT (in a few cases, a crop might be disaggregated in additional categories in the trade data, for example, soy can be categorized as soy cake, soy powder and soy "in natura"). Since the data on revenues capture farm production, instead of revenues generated by processing industries, we pick the codes associated with trade in less processed goods. For example, for oil palm production we do not include data on bilateral trade flows in palm oil.

Lastly, for the non-agriculture and agriculture sector, we also constructed data on trade flows and gross output for 1980, which we use in the paper to measures changes in trade costs and productivity between 1980 and 2007. In this case, we adopt the same procedure as the one used earlier, but we instead bring in bilateral trade flow data from Feenstra, Lipsey, Deng, Ma, and Mo (2005), which is also based on COMTRADE, given that data from BACI is not available for earlier years.

Consumption Share and Labor Employment. To construct our data on consumption share in agricultural goods, we collect data from different sources. For developing countries, we use data from the Global Consumption database organized by the World Bank to construct the consumption shares in agricultural goods. For the United States, we use data from the consumer expenditure survey. For Canada, we use data from household surveys available from Queen's University of Canada. For European countries, we bring data from Eurostat. To construct labor employment, we use data from UN-ILO. When data from UN-ILO was not available, we infer the share of workers in agriculture using data on the share of workers in rural areas from the World Bank.

B Additional Empirical Patterns

In the main body of the article, we discussed key relationships between economic development and agricultural input intensity. This section discusses three additional empirical patterns that motivate our modeling approach and are important for understanding the effects of globalization in our counterfactual analyses. The additional patterns are summarized in Figure A.1.

Panel (a) shows that the labor share in agriculture falls substantially with the level of economic development. This is consistent with high-income countries employing more input-intensive technologies for agricultural production.

Panel (b) documents that the share of final expenditure in agricultural goods falls with the level of economic development. This is a feature of economic development that has long been discussed in the literature.We capture this relationship in out model using a non-homothetic CES.

Panel (c) shows that the share of exports of agricultural goods from total exports tends to be larger for countries with lower levels of income. For example, in Ethiopia almost 80% of the exports are from the agricultural sector, whereas in Sweden this share is only 2.5%. This indicates that agricultural sector is important not only because it accounts for an important share of the internal value added, but also because it is a large share of export revenues in low-income countries, and it allows some of high-income countries to import non-agriculture goods.

Panel (d) plots the data on average normalized yield against agricultural input cost share across countries. The positive correlation indicates that land productivities are larger in countries where the intensity of input use in agricultural production is larger.

C Details of the Theory

This section presents our theoretical derivations. Section C.1 concerns the unit cost of production and output. Section C.2 derives the expressions associated with the fixed costs of production. Sections C.3-C.4 present in details the derivations from our generalized Fréchet distribution for choice probabilities and average productivities conditional on selection. Section C.5 shows the derivations used to study the production possibility frontier. Lastly, Section C.6 concerns the formulas for the gains from trade.

C.1 Costs and Output

Unit cost. Focusing on production in a plot given a choice of agriculture activity, we drop country-field-crop-technology indicators, and write down the cost minimization problem:

$$\min_{L\geq 0, N\geq 0, M\geq 0} \; rL + wN + mM \quad s.t. \quad \bar{q}\Big(zL\Big)^{\gamma^L}\Big(N\Big)^{\gamma^N}\Big(M\Big)^{\gamma^M} = 1,$$

where

$$\bar{q} \equiv (\gamma^L)^{-\gamma^L}(\gamma^N)^{-\gamma^N}(\gamma^M)^{-\gamma^M}.$$

The Lagrangian function is:

$$\mathcal{L} = rL + wN + mM - \mu\Big[\bar{q}\Big(zL\Big)^{\gamma^L}\Big(N\Big)^{\gamma^N}\Big(M\Big)^{\gamma^M} - 1\Big].$$

First order conditions are:

$$\begin{aligned} r &= \mu\bar{q}\gamma^L z^{\gamma^L} L^{\gamma^L-1} N^{\gamma^N} I^{\gamma^M} \\ w &= \mu\bar{q}\gamma^N z^{\gamma^L} L^{\gamma^L} N^{\gamma^N-1} I^{\gamma^M} \\ m &= \mu\bar{q}\gamma^M z^{\gamma^L} L^{\gamma^L} N^{\gamma^N} I^{\gamma^M-1} \end{aligned}$$

The employment of labor and land relative to inputs are then given by:

$$\frac{rL}{mM} = \frac{\gamma^L}{\gamma^M} \to L = \frac{\gamma^L}{\gamma^M}\frac{mM}{r}, \;\; \frac{wN}{mM} = \frac{\gamma^N}{\gamma^M} \to N = \frac{\gamma^N}{\gamma^M}\frac{mM}{w}.$$

Replace L and N into the production equation, $\bar{q}\Big(z\frac{\gamma^L}{\gamma^M}\frac{mM}{r}\Big)^{\gamma^L}\Big(\frac{\gamma^N}{\gamma^M}\frac{mM}{w}\Big)^{\gamma^N}\Big(M\Big)^{\gamma^M} = 1$, delivers:

$$M = (\bar{q})^{-1} z^{-\gamma^L}(\gamma^L)^{-\gamma^L}(\gamma^N)^{-\gamma^N}(\gamma^M)^{1-\gamma^M} r^{\gamma^L} w^{\gamma^N} m^{\gamma^M-1},$$

which then results:

$$M = (r/z)^{\gamma^L} w^{\gamma^N} m^{\gamma^M}\frac{\gamma^M}{m}, \quad L = (r/z)^{\gamma^L} w^{\gamma^N} m^{\gamma^M}\frac{\gamma^L}{r}, \text{ and } \quad N = (r/z)^{\gamma^L} w^{\gamma^N} m^{\gamma^M}\frac{\gamma^N}{w}.$$

Using these optimal choices of inputs, the unit cost of production equals

$$c = rL + wN + mM = (r/z)^{\gamma^L} w^{\gamma^N} m^{\gamma^M}.$$

Rent. Combining zero profit condition and returns to land,

$$c = p \Rightarrow (r/z)^{\gamma^L} w^{\gamma^N} m^{\gamma^M} = p,$$

which results:

$$r = zp^{\frac{1}{\gamma^L}} w^{-\frac{\gamma^N}{\gamma^L}} m^{-\frac{\gamma^M}{\gamma^L}}$$

Output. The size of each plot of land is w.l.o.g. normalized to one, and it is optimal to use the entire plot as long as profits are non-negative. Therefore, land use L equals one. It follows that:

$$\begin{aligned} N &= \frac{rL}{w}\frac{\gamma^N}{\gamma^L} = zp^{\frac{1}{\gamma^L}} w^{-\frac{\gamma^N}{\gamma^L}} m^{-\frac{\gamma^M}{\gamma^L}} \frac{\gamma^N}{w\gamma^L} \\ M &= \frac{rL}{m}\frac{\gamma^M}{\gamma^L} = zp^{\frac{1}{\gamma^L}} w^{-\frac{\gamma^N}{\gamma^L}} m^{-\frac{\gamma^M}{\gamma^L}} \frac{\gamma^M}{m\gamma^L}. \end{aligned}$$

Replace N, M, and $L = 1$ into the production equation gives output at the plot level:

$$Q = \bar{q}\Big(zL\Big)^{\gamma^L}\Big(N\Big)^{\gamma^N}\Big(M\Big)^{\gamma^M} = \bar{q}\Big(z\Big)^{\gamma^L}\Big(zp^{\frac{1}{\gamma^L}} w^{-\frac{\gamma^N}{\gamma^L}} m^{-\frac{\gamma^M}{\gamma^L}}\Big)^{\gamma^N+\gamma^M}\Big(\frac{\gamma^N}{w\gamma^L}\Big)^{\gamma^N}\Big(\frac{\gamma^M}{m\gamma^L}\Big)^{\gamma^M}.$$

Since $\bar{q} \equiv (\gamma^L)^{-\gamma^L}(\gamma^N)^{-\gamma^N}(\gamma^M)^{-\gamma^M}$, and $\gamma^L + \gamma^N + \gamma^M = 1$,

$$Q = z\Big(\gamma^L\Big)^{-1}\Big(\frac{w}{p}\Big)^{-\gamma^N/\gamma^L}\Big(\frac{m}{p}\Big)^{-\gamma^M/\gamma^L}.$$

C.2 Quantity of fixed costs

The unconditional mean of investment intensity draw, $s_i^f(\omega)$, is given by

$$\mathbb{E}\Big[a_{i,0}^f(\omega)\Big] = a_{i,0}^f.$$

Let Ω_i^f be the set of plots within field f which are selected for agriculture use. The share of land allocated to all agricultural uses is denoted by α_i^f,

$$\alpha_i^f \equiv \Pr(\omega \in \Omega_i^f) = \sum_{k\in\mathcal{K}} \alpha_{i,k}^f.$$

The mean of $a_{i,0}^f(\omega)$ conditional on plot ω not being selected for agriculture is

$$\mathbb{E}\Big[a_{i,0}^f(\omega) \mid \omega \notin \Omega_i^f\Big] = a_{i,0}^f(1-\alpha_i^f)^{-1/\theta_1}.$$

The conditional mean is greater than the unconditional mean because when the investment intensity of a plot is too large, it will be less likely to select that plot for agriculture. By relating conditional and unconditional means and rearranging the resulting terms,

$$\begin{aligned}
\mathbb{E}\Big[a^f_{i,0}(\omega)\Big] &= \mathbb{E}\Big[a^f_{i,0}(\omega) \mid \omega \in \Omega^f_i\Big] \Pr(\omega \in \Omega^f_i) + \mathbb{E}\Big[a^f_{i,0}(\omega) \mid \omega \notin \Omega^f_i\Big] \Pr(\omega \notin \Omega^f_i) \\
\mathbb{E}\Big[a^f_{i,0}(\omega) \mid \omega \in \Omega^f_i\Big] &= \frac{1}{\Pr(\omega \in \Omega^f_i)} \Bigg[\mathbb{E}\Big[a^f_{i,0}(\omega)\Big] - \mathbb{E}\Big[a^f_{i,0}(\omega) \mid \omega \notin \Omega^f_i\Big] \Pr(\omega \notin \Omega^f_i)\Bigg] \\
\mathbb{E}\Big[a^f_{i,0}(\omega) \mid \omega \in \Omega^f_i\Big] &= \frac{1}{\alpha^f_i}\Big[a^f_{i,0} - a^f_{i,0}(1-\alpha^f_i)^{-1/\theta_1}(1-\alpha^f_i)\Big] \\
\mathbb{E}\Bigg[a^f_{i,0}(\omega) \mid \omega \in \Omega^f_i\Bigg] &= \frac{a^f_{i,0}}{\alpha^f_i}\Bigg[1 - (1-\alpha^f_i)^{(\theta_1-1)/\theta_1}\Bigg].
\end{aligned}$$

The field-level quantity required for fixed investments in agriculture, S^f_i, equals the average fixed cost requirement conditional on plots being used for agriculture times the number of plots used for agriculture, $S^f_i = \mathbb{E}\Bigg[a^f_{i,0}(\omega) \mid \omega \in \Omega^f_i\Bigg]\alpha^f_i L^f_i$. Replacing in this equation the above one reproduces equation (10) of the main text,

$$S^f_i = a^f_{i,0} L^f_i \Bigg[1 - (1-\alpha^f_i)^{(\theta_1-1)/\theta_1}\Bigg].$$

C.3 Choice Probabilities with Generalized Extreme Value Distributions

We invoke a theorem from McFadden (1981) to derive choice probabilities when draws are from generalized extreme value (EV) distributions, including Fréchet (type II EV).

C.3.1 McFadden's Theorem

We start by reviewing Theorem 5.2 in "Econometric Models of Probabilistic Choice" by McFadden (1981). Consider the following discrete choice problem:

$$\max_{i \in \Omega} \quad -q_i + u_i$$

where Ω is the set of alternatives, q_i is the non-stochastic component of the objective function, and u_i is a stochastic term. For example, it is well-known that if $q_i = -\mathbf{b}'\mathbf{z}_i$, and u_i is a random variable drawn independently from type I extreme value distribution, $F(u) = \exp(-e^{-u})$, then the choice probabilities are given by $\pi_i = \frac{e^{-q_i}}{\sum_{j \in \Omega} e^{-q_j}} = \frac{e^{\mathbf{b}'\mathbf{z}_i}}{\sum_{j \in \Omega} e^{\mathbf{b}'\mathbf{z}_j}}$

Theorem. *Given $\Omega = \{1, ..., m\}$, consider $H(\mathbf{y})$ with $\mathbf{y} = (y_1, ..., y_m)$ such that:*

1. $H(\mathbf{y})$ is non-negative, and it is homogeneous of degree one.
2. $H(\mathbf{y}) \to \infty$ as $y_i \to \infty$ for all $i \in \Omega$.
3. The mixed partial derivatives of H exist and are continuous, with non-positive even and non-negative odd mixed partial derivatives.

Then,

1. The following function

$$F(\boldsymbol{u}) = \exp\Bigg[-H\Big(e^{-u_1}, ..., e^{-u_m}\Big)\Bigg]$$

is a multivariate extreme value distribution.

2. Choice probabilities satisfy

$$\pi_i(\mathbf{q}) = -\frac{\partial}{\partial q_i} \ln H\Big(e^{-q_1}, ..., e^{-q_m}\Big)$$

We will use this theorem in our derivations below. For illustrative purposes, we first begin with applying the theorem to a choice structure with one nest. Then, we focus on a two-nest structure, that is the one in our framework.

C.3.2 Discrete Choices With One Nest

Suppose H is given by

$$H(\mathbf{y}) = \Big[\sum_{k\in\Omega} y_k^{\rho}\Big]^{1/\rho}$$

With $\rho = \frac{1}{1-\sigma}$, as long as $0 \leq \sigma < 1$, the conditions in the above theorem are satisfied. Let $\Omega = \{1, ..., K\}$. According to the first result of the theorem, the following is a multivariate EV distribution:

$$F(\mathbf{u}) = \exp\Bigg[-\Big(e^{-\rho u_1} + ... + e^{-\rho u_K}\Big)^{1/\rho}\Bigg], \tag{C.1}$$

where σ is the correlation parameter between $(u_j, u_{j'})$. According to the second result of the theorem, choice probabilities are:

$$\pi_k = -\frac{\partial}{\partial q_k} \ln\Big(e^{-\rho q_1} + ... + e^{-\rho q_K}\Big)^{1/\rho} = \frac{e^{-\rho q_k}}{e^{-\rho q_1} + ... + e^{-\rho q_K}} \tag{C.2}$$

By a change of variables, we can specify draws based on Type II EV (Fréchet) rather than Type I EV. Recall that the discrete choice problem as originally formulated in McFadden's theorem was: $[\max_{k\in\Omega}(-q_k + u_k)]$. This problem is equivalent to:

$$\max_{k\in\Omega} \quad h_k z_k,$$

where $q_k = -\theta \ln h_k a_k$, and $u_k = \theta \ln(z_k/a_k)$. Here, h_k is the non-stochastic component and z_k is a draw from a probability distribution. Replacing z_k for u_k in (C.1), the probability distribution of $\mathbf{z}(\omega) = (z_1(\omega), ..., z_K(\omega))$ is:

$$\Pr(z_1(\omega) \leq z_1, ..., z_K(\omega) \leq z_K) \equiv F(z_1, ..., z_K) = \exp\Bigg[-\Big(\sum_{k=1}^{K}(z_k/a_k)^{-\theta\rho}\Big)^{\frac{1}{\rho}}\Bigg], \tag{C.3}$$

which is a Fréchet (Type II EV) distribution. Replacing for $q_k = -\theta \ln h_k a_k$ in (C.2), choice probabilities are:

$$\pi_k = \frac{(h_k a_k)^{\theta\rho}}{\sum_{k=1}^{K}(h_k a_k)^{\theta\rho}} \tag{C.4}$$

The case of Eaton and Kortum (2002) with independent draws is a special case in which $\rho = 1$ (or equivalently, $\sigma = 0$), and so, $z_1(\omega)$, ..., $z_K(\omega)$ are independent. The probability distribution simplifies to

$$F(z_1, ..., z_K) = \exp\Bigg[-\Big(\sum_{k=1}^{K}(z_k/a_k)^{-\theta}\Big)\Bigg].$$

Thanks to independence of $z_1(\omega)$, ..., $z_K(\omega)$, the distribution of $z_k(\omega)$ equals

$$\Pr(z_k(\omega) \le z_k) \equiv F_k(z_k) = F(\infty, ...\infty, z_K, \infty, ...\infty) = \exp\Big[-(z_k/a_k)^{-\theta}\Big],$$

which is the distribution used in EK. In addition, setting $\rho = 1$ implies choice probabilities: $\pi_k = \frac{(h_k a_k)^\theta}{\sum_{k=1}^K (h_k a_k)^\theta}$.

C.3.3 Discrete Choices With Two Nests

The following function H satisfies the conditions in McFadden's theorem,

$$H(\mathbf{y}) = \sum_{k=1}^K \Big[\sum_{\tau\in\Omega_k} y_{k\tau}^\rho\Big]^{1/\rho}$$

Using the first result of the theorem, the following is a multivariate EV distribution

$$F(\mathbf{u}) = \exp\left[-\sum_{k=1}^K \Big[\sum_{\tau\in\Omega_k} e^{-\rho u_{k\tau}}\Big]^{1/\rho}\right] \tag{C.5}$$

and, choice probabilities are as follows, based on the second result of the theorem,

$$\pi_{k\tau} = -\frac{\partial}{\partial q_{k\tau}} \ln\left[\sum_{k=1}^K \Big[\sum_{\tau\in\Omega_k} e^{-\rho q_{k\tau}}\Big]^{1/\rho}\right] = \frac{e^{-\rho q_{k\tau}}}{\sum_{\tau\in\Omega_k} e^{-\rho q_{k\tau}}} \times \frac{\Big[\sum_{\tau\in\Omega_k} e^{-\rho q_{k\tau}}\Big]^{1/\rho}}{\sum_{k=1}^K \Big[\sum_{\tau\in\Omega_k} e^{-\rho q_{k\tau}}\Big]^{1/\rho}} \tag{C.6}$$

The following changes of variables convert the formulation from EV type I to EV type II distribution: $q_{k\tau} = -\theta \ln(a_{k\tau} h_{k\tau})$ and $u_{k\tau} = \theta \ln(z_{k\tau}/a_{k\tau})$. Replacing these in (C.5) and (C.8) delivers the distribution function of $\mathbf{z} = \{z_{k\tau}\}_{k\tau}$ and choice probabilities:

$$F(\mathbf{z}) = \exp\left[-\sum_{k=1}^K \Big[\sum_{\tau\in\Omega_k} (z_{k\tau}/a_{k\tau})^{-\theta\rho}\Big]^{1/\rho}\right] \tag{C.7}$$

$$\pi_{k\tau} = \frac{(a_{k\tau}h_{k\tau})^{\theta\rho}}{\sum_{\tau\in\Omega_k}(a_{k\tau}h_{k\tau})^{\theta\rho}} \times \frac{\Big[\sum_{\tau\in\Omega_k}(a_{k\tau}h_{k\tau})^{\theta\rho}\Big]^{1/\rho}}{\sum_{k=1}^K \Big[\sum_{\tau\in\Omega_k}(a_{k\tau}h_{k\tau})^{\theta\rho}\Big]^{1/\rho}} \tag{C.8}$$

The connection from the above equation to the ones that describe land shares in the main text is immediate. By setting $\theta_2 = \rho\theta$ and $\theta_1 = \theta$, the above readily delivers the four equations 2-3-4-5 ,

$$\pi_{k\tau} = \underbrace{\frac{(h_{k\tau}a_{k\tau})^{\theta_2}}{H_k^{\theta_2}}}_{\alpha_{k\tau}} \underbrace{\frac{H_k^\theta}{\sum_k H_k^\theta}}_{\alpha_k} \quad \text{where} \quad H_k = \Big[\sum_{\tau=1}^T (h_{k\tau}a_{k\tau})^{\theta_2}\Big]^{\frac{1}{\theta_2}}$$

C.4 Expected Value Conditional on Selection

In this section, we derive expected values of returns to land conditional on selections based on discrete choices. These derivations deliver average land productivities in our model conditional on choices of crop-technology pairs. Again, for a clearer illustration, we first present the derivation for the case with one nest, then we move to the two-nest distribution which is the case in our framework.

C.4.1 One Nest

Reproducing equations (C.3) and (C.4),

$$\Pr(z_1(\omega) \leq z_1, ..., z_K(\omega) \leq z_K) \equiv F(z_1, ..., z_K) = \exp\Bigg[- \Big(\sum_{k=1}^{K} (z_k/a_k)^{-\theta\rho} \Big)^{\frac{1}{\rho}} \Bigg]$$

$$\pi_k = \frac{(h_k a_k)^{\theta\rho}}{\sum_{k=1}^{K} (h_k a_k)^{\theta\rho}}$$

For notational simplicity, and w.l.o.g. we focus on the choice probability of the 1st alternative ($k = 1$). Let $\Omega_j = \{\omega : h_j z_j(\omega) = \max_k \quad h_k z_k(\omega), \ \ k = 1, ..., K\}$. Define

$$F^1(z_1, ..., z_K) \equiv \frac{\partial}{\partial z_1} F(z_1, ..., z_K)$$

which equals:

$$F^1(z_1, ..., z_K) = \theta a_1^{\theta\rho} z_1^{-\theta\rho-1} \Big(\sum_{k=1}^{K} (z_k/a_k)^{-\theta\rho} \Big)^{\frac{1}{\rho}-1} \exp\Bigg[- \Big(\sum_{k=1}^{K} (z_k/a_k)^{-\theta\rho} \Big)^{\frac{1}{\rho}} \Bigg]$$

The probability distribution of $z_1(\omega)$ conditional on selecting the 1st alternative, $\omega \in \Omega_1$,

$$\begin{aligned}
\widetilde{F}_1(z) &\equiv \Pr\Big(z_1(\omega) \leq z \mid \omega \in \Omega_1 \Big) \\
&= \frac{1}{\Pr(\omega \in \Omega_1)} \Pr\Big(z_1(\omega) \leq z, \ h_1 z_1(\omega) \geq h_j z_j(\omega) \Big) \\
&= \frac{1}{\pi_1} \Pr\Big(z_1(\omega) \leq z, \ z_j(\omega) \leq \frac{h_1}{h_j} z_1(\omega) \Big) \\
&= \frac{1}{\pi_1} \int_{z_1=0}^{z} \int_{z_2=0}^{\frac{h_1}{h_2} z_1} \int_{z_K=0}^{\frac{h_1}{h_K} z_1} f(z_1, z_2, ..., z_K) dz_K ... dz_2 dz_1 \\
&= \frac{1}{\pi_1} \int_{z_1=0}^{z} F^1(z_1, \frac{h_1}{h_2} z, ..., \frac{h_1}{h_K} z_1) dz_1 \\
&= \frac{1}{\pi_1} \int_{z_1=0}^{z} \theta a_1^{\theta\rho} z_1^{-\theta\rho-1} \Big((\frac{z_1}{a_1})^{-\theta\rho} + \sum_{k=2}^{K} (\frac{h_1 z_1}{h_k a_k})^{-\theta\rho} \Big)^{\frac{1}{\rho}-1} \exp\Bigg[- \Big((\frac{z_1}{a_1})^{-\theta\rho} + \sum_{k=2}^{K} (\frac{h_1 z_1}{h_k a_k})^{-\theta\rho} \Big)^{\frac{1}{\rho}} \Bigg] dz_1 \\
&= \frac{1}{\pi_1} \int_{z_1=0}^{z} \theta a_1^{\theta} z_1^{-\theta-1} \Big(1 + \sum_{k=2}^{K} (\frac{h_1 a_1}{h_k a_k})^{-\theta\rho} \Big)^{\frac{1}{\rho}-1} \exp\Bigg[- z^{-\theta} a_1^{\theta} \Big(1 + \sum_{k=2}^{K} (\frac{h_1 a_1}{h_k a_k})^{-\theta\rho} \Big)^{\frac{1}{\rho}} \Bigg] dz_1 \\
&= \frac{1}{\pi_1} \int_{z_1=0}^{z} \theta a_1^{\theta} z_1^{-\theta-1} \Big((h_1 a_1)^{-\theta\rho} \sum_{k=1}^{K} (h_k a_k)^{\theta\rho} \Big)^{\frac{1}{\rho}-1} \exp\Bigg[- z_1^{-\theta} a_1^{\theta} \Big((h_1 a_1)^{-\theta\rho} \sum_{k=1}^{K} (h_k a_k)^{\theta\rho} \Big)^{\frac{1}{\rho}} \Bigg] dz_1 \\
&= \int_{z_1=0}^{z} \theta a_1^{\theta} z_1^{-\theta-1} \Big(\frac{1}{\pi_1} \Big)^{\frac{1}{\rho}} \exp\Bigg[- z_1^{-\theta} a_1^{\theta} \Big(\frac{1}{\pi_1} \Big)^{\frac{1}{\rho}} \Bigg] dz_1
\end{aligned}$$

The last line is a Fréchet distribution with c.d.f. $\exp(-T z_1^{-\theta})$ with location parameter $T = a_1^{\theta} \pi_1^{-1/\rho}$. It is straightforward to show that the expected value of this Fréchet distribution equals $\Gamma(1 - 1/\theta) T^{1/\theta}$.

Putting together, the expected value of $z_1(\omega)$ conditional on $\omega \in \Omega_1$ equals

$$\mathbb{E}\Big(z_1(\omega)|\ \omega \in \Omega_1\Big) = \Gamma(1-1/\theta)a_1\pi_1^{-1/\theta\rho}$$

To make a closer connection to the notation we adopted in the main text, let $\theta_2 \equiv \theta\rho$, and $\theta_1 \equiv \theta$. Then,

$$\Pr(z_1(\omega) \leq z_1, ..., z_K(\omega) \leq z_K) = \exp\left[-\Big(\sum_{k=1}^{K}(z_k/a_k)^{-\theta_2}\Big)^{\frac{\theta_1}{\theta_2}}\right]$$

And, the conditional expected value is given by

$$\mathbb{E}\Big(z_1(\omega)|\ \omega \in \Omega_1\Big) = \Gamma(1-1/\theta_1)a_1\pi_1^{-1/\theta_2}$$

Note that, as in the main text, we could specify the distribution function by shifting the scale of draws according to some scalar $\bar{\phi} > 0$,

$$\Pr(z_1(\omega) \leq z_1, ..., z_K(\omega) \leq z_K) = \exp\left[-\bar{\phi}\Big(\sum_{k=1}^{K}(z_k/a_k)^{-\theta_2}\Big)^{\frac{\theta_1}{\theta_2}}\right]$$

In this case, the conditional expected value equals: $\mathbb{E}\Big(z_1(\omega)|\ \omega \in \Omega_1\Big) = \Gamma(1-1/\theta_1)(\bar{\phi})^{1/\theta_1}a_1\pi_1^{-1/\theta_2}$ and the unconditional mean equals: $\mathbb{E}\Big(z_1(\omega)\Big) = \Gamma(1-1/\theta_1)(\bar{\phi})^{1/\theta_1}a_1$. By choosing $\bar{\phi} = [\Gamma(1-1/\theta_1)]^{-\theta_1}$, we then ensure that $\mathbb{E}\Big(z_1(\omega)|\ \omega \in \Omega_1\Big) = a_1\pi_1^{-1/\theta_2}$ and $\mathbb{E}\Big(z_1(\omega)\Big) = a_1$.

C.4.2 Two Nests

We now turn to the generalized Fréchet distribution we have adopted in the text. For the sake of a clear derivation, compared to the main text, we set the value of the outside option (i.e. the option of not using a plot for agriculture) to zero. The alternatives in the upper nest are given by $\{1, ..., K\}$ and in the lower nest within each k by $\{1, ..., T\}$. Using equation (C.7) , we can express the generalized Fréchet distribution as:

$$F(\mathbf{z}) = \exp\left[-\bar{\phi}\sum_{k=1}^{K}\Big[\sum_{\tau=1}^{T}(z_{k\tau}/a_{k\tau})^{-\theta\rho}\Big]^{1/\rho}\right]$$

where $\mathbf{z} = [(z_{11}, ..., z_{1T}), ..., (z_{k1}, ..., z_{kT}), ...(z_{K1}, ..., z_{KT})]$ with $z_{k\tau}$ referring to the land productivity draw of crop-technology pair $k\tau$, and $\bar{\phi} = [\Gamma(1-1/\theta)]^{-\theta}$ is a scalar. Using equation (C.8), the choice probability of $k\tau$ equals:

$$\pi_{k\tau} = \frac{(h_{k\tau}a_{k\tau})^{\theta\rho}}{H_k^{\theta\rho}}\frac{H_k^{\theta}}{H_1^{\theta}+...+H_K^{\theta}}, \quad \text{where} \quad H_k = \Big[(h_{k1}a_{k1})^{\theta\rho}+...+(h_{kT}a_{kT})^{\theta\rho}\Big]^{\frac{1}{\theta\rho}}.$$

For notational simplicity and w.o.l.g, we focus on the choice of $(k', \tau') = (1, 1)$. Defining $F^{11}(\mathbf{z}) \equiv \frac{\partial}{\partial z_{11}}F(\mathbf{z})$, we have:

$$F^{11}(\mathbf{z}) \quad = \quad \bar{\phi}\theta a_{11}^{\theta\rho}z_{11}^{-\theta\rho-1}\Big(\sum_{\tau=1}^{T}(z_{1\tau}/a_{1\tau})^{-\theta\rho}\Big)^{\frac{1}{\rho}-1}\exp\left[-\bar{\phi}\sum_{k=1}^{K}\Big[\sum_{\tau=1}^{T}(z_{k\tau}/a_{k\tau})^{-\theta\rho}\Big]^{1/\rho}\right]$$

The probability distribution of $z_{11}(\omega)$ conditional on $\omega \in \Omega_{11}$ is then given by:

$$\begin{aligned}
\widetilde{F}_{11}(z) &\equiv \Pr\Big(z_{11}(\omega) \le z \mid \omega \in \Omega_{11}\Big) \\
&= \frac{1}{\Pr(\omega \in \Omega_{11})} \Pr\Big(z_{11}(\omega) \le z,\ h_{k\tau} z_{k\tau}(\omega) \le h_{11} z_{11}(\omega)\Big) \\
&= \frac{1}{\pi_{11}} \Pr\Big(z_{11}(\omega) \le z,\ z_{k\tau}(\omega) \le \frac{h_{11}}{h_{k\tau}} z_{11}(\omega)\Big) \\
&= \frac{1}{\pi_{11}} \int_{\tilde{z}=0}^{z} F^{11}(\tilde{z}\frac{h_{11}}{h_{11}}, \frac{h_{11}}{h_{12}}\tilde{z}, ..., \frac{h_{11}}{h_{1T}}\tilde{z}, ..., \frac{h_{11}}{h_{K1}}\tilde{z}, ..., \frac{h_{11}}{h_{KT}}\tilde{z}) d\tilde{z} \\
&= \frac{1}{\pi_{11}} \int_{\tilde{z}=0}^{z} \bar{\phi}\theta a_{11}^{\theta\rho} \tilde{z}^{-\theta\rho-1} \Big(\sum_{\tau=1}^{T} (\frac{h_{11}\tilde{z}}{h_{1\tau}a_{1\tau}})^{-\theta\rho}\Big)^{\frac{1}{\rho}-1} \exp\Bigg[-\bar{\phi}\sum_{k=1}^{K}\Big[\sum_{\tau=1}^{T}(\frac{h_{11}\tilde{z}}{h_{k\tau}a_{k\tau}})^{-\theta\rho}\Big]^{1/\rho}\Bigg] d\tilde{z} \\
&= \frac{1}{\pi_{11}} \int_{\tilde{z}=0}^{z} \bar{\phi}\theta a_{11}^{\theta} \tilde{z}^{-\theta-1} \Big(\sum_{\tau=1}^{T} (\frac{h_{11}a_{11}}{h_{1\tau}a_{1\tau}})^{-\theta\rho}\Big)^{\frac{1}{\rho}-1} \exp\Bigg[-\bar{\phi}\tilde{z}^{-\theta} a_{11}^{\theta}\sum_{k=1}^{K}\Big[\sum_{\tau=1}^{T}(\frac{h_{11}a_{11}}{h_{k\tau}a_{k\tau}})^{-\theta\rho}\Big]^{1/\rho}\Bigg] d\tilde{z} \\
&= \frac{1}{\pi_{11}} \int_{\tilde{z}=0}^{z} \bar{\phi}\theta a_{11}^{\theta} \tilde{z}^{-\theta-1} \Big((h_{11}a_{11})^{-\theta\rho} \sum_{\tau=1}^{T} (h_{1\tau}a_{1\tau})^{\theta\rho}\Big)^{\frac{1}{\rho}-1} \\
&\quad \times \exp\Bigg[-\bar{\phi}\tilde{z}^{-\theta} a_{11}^{\theta}\sum_{k=1}^{K}\Big[(h_{11}a_{11})^{-\theta\rho}\sum_{\tau=1}^{T}(h_{k\tau}a_{k\tau})^{\theta\rho}\Big]^{1/\rho}\Bigg] d\tilde{z}
\end{aligned}$$

Using $H_k \equiv \Big(\sum_{\tau=1}^{T}(h_{k\tau}a_{k\tau})^{\theta\rho}\Big)^{1/\theta\rho}$, and $\pi_{11} = \frac{(h_{11}a_{11})^{\theta\rho}}{H_1^{\theta\rho}} \frac{H_1^{\theta}}{\sum_{k=1}^{K} H_k^{\theta}}$, we simplify the last line into the following:

$$\widetilde{F}_{11}(z) = \int_{\tilde{z}=0}^{z} \bar{\phi}\theta a_{11}^{\theta} \tilde{z}^{-\theta-1} \Big((h_{11}a_{11})^{-\theta} \sum_{k=1}^{K} H_k^{\theta}\Big) \exp\Bigg[-\bar{\phi}\tilde{z}^{-\theta} a_{11}^{\theta} (h_{11}a_{11})^{-\theta} \sum_{k=1}^{K} H_k^{\theta}\Bigg].$$

Inspecting the above equation, it becomes evident that the distribution of $z_{11}(\omega)$ conditional on $\omega \in \Omega_{11}$ is a Fréchet with c.d.f $\widetilde{F}_{11}(z) = \exp(-Tz^{-\theta})$ where the location parameter T equals $\bar{\phi}a_{11}^{\theta}\Big((h_{11}a_{11})^{-\theta}\sum_{k=1}^{K} H_k^{\theta}\Big)$. It is straightforward to check that the expected value of a Fréchet distributed random variable with c.d.f. $\exp(-Tz^{-\theta})$ equals $\Gamma(1-1/\theta)T^{1/\theta}$. Hence,

$$\begin{aligned}
\mathbb{E}(z_{11}(\omega)|\omega \in \Omega_{11}) = &\quad \Gamma(1-1/\theta)\left(\bar{\phi}a_{11}^{\theta}\Big((h_{11}a_{11})^{-\theta}\textstyle\sum_{k=1}^{K} H_k^{\theta}\Big)\right)^{1/\theta} \\
&\Gamma(1-1/\theta)\,(\bar{\phi})^{1/\theta}\, a_{11} \left(\frac{(h_{11}a_{11})^{\theta\rho}}{H_1^{\theta\rho}}\right)^{-1/\theta\rho} \left(\frac{H_1^{\theta}}{\sum_{k=1}^{K} H_k^{\theta}}\right)^{-1/\theta}
\end{aligned}$$

Notice that for the sake of tracking a clearer notation and with no loss of generality, we calculated the conditional expected value of crop-technology $(k,\tau) = (1,1)$. Writing the expression for (k,τ), noting that $\bar{\phi} = [\Gamma(1-1/\theta)]^{-\theta}$, and setting $\theta_2 = \theta\rho$ and $\theta_1 = \theta$,

$$\mathbb{E}(z_{k\tau}(\omega)|\omega \in \Omega_{k\tau}) = a_{k\tau} \left(\underbrace{\frac{(h_{k\tau}a_{k\tau})^{\theta_2}}{H_k^{\theta_2}}}_{\alpha_{k\tau}}\right)^{-1/\theta_2} \left(\underbrace{\frac{H_k^{\theta_1}}{\sum_{k=1}^{K} H_k^{\theta_1}}}_{\alpha_k}\right)^{-1/\theta_1}.$$

This derivation delivers the average land productivities conditional on the selection of a crop-technology pair as given by equation (6).

C.5 Derivations for Recasting the Micro-founded Structure to an Aggregate Problem of PPF

In this section, we recast the land use problem onto crop supply through the lens of production possibility frontiers. We show that (i) the aggregate problem which describe below, reproduces equation (8), and (ii) the Lagrange multipliers of this problem reproduce returns to land. Recalling that $h_{i,k\tau} = p_{i,k}\widetilde{h}_{i,k\tau}$and using an equivalent notation where $Q^f_{i,k\tau} = (\gamma^L_{k\tau})^{-1}\widetilde{h}_{i,k\tau}\widetilde{L}^f_{i,k\tau}$, and $\widetilde{Q}^f_{i,k} = \widetilde{L}^f_{i,k}$, the problem of the agricultural producer in Section 4.1 can be written as:

$$
\begin{array}{ll}
\max\limits_{\{Q^f_{i,k\tau}\}_{k,\tau}\ ,\ \{\widetilde{Q}^f_{i,k}\}_k} & \sum_{\tau\in\mathcal{T}}\sum_{k\in\mathcal{K}}\gamma^L_{k\tau}p_{i,k}Q^f_{i,k\tau} \\
\text{subject to} & \left[\sum_{\tau\in\mathcal{T}}\left(\frac{Q^f_{i,k\tau}}{v^f_{i,k\tau}}\right)^{\frac{\theta_2}{\theta_2-1}}\right]^{\frac{\theta_2-1}{\theta_2}} \le \widetilde{Q}^f_{i,k} \\
 & \left[\sum_{k\in\mathcal{K}}(\widetilde{Q}^f_{i,k})^{\frac{\theta_1}{\theta_1-1}}\right]^{\frac{\theta_1-1}{\theta_1}} \le L^f_i
\end{array}
\tag{C.9}
$$

where

$$
v^f_{i,k\tau} = (\gamma^L_{k\tau})^{-1}\widetilde{h}_{i,k\tau}a^f_{i,k\tau}. \tag{C.10}
$$

The Lagrangian function associated with this maximization problem is:

$$
\mathcal{L} = \sum_\tau\sum_k\gamma^L_{k\tau}p_{i,k}Q^f_{i,k\tau} - \lambda^f_{i,k}\left\{\left[\sum_\tau\left(\frac{Q^f_{i,k\tau}}{v^f_{i,k\tau}}\right)^{\frac{\theta_2}{\theta_2-1}}\right]^{\frac{\theta_2-1}{\theta_2}} - \widetilde{Q}^f_{i,k}\right\} - \mu^f_i\left\{\left[\sum_k(\widetilde{Q}^f_{i,k})^{\frac{\theta_1}{\theta_1-1}}\right]^{\frac{\theta_1-1}{\theta_1}} - L^f_i\right\}
$$

Provided that the solution is interior, and quantities are all positive, the first order conditions require that:

$$
\gamma^L_{k\tau}p_{i,k} = \mu^f_{i,k}(v^f_{i,k\tau})^{-\frac{\theta_2}{\theta_2-1}}(Q^f_{i,k\tau})^{\frac{1}{\theta_2-1}}(\widetilde{Q}^f_{i,k})^{-\frac{1}{\theta_2-1}} \tag{C.11}
$$

$$
\mu^f_{i,k} = \mu^f_i(\widetilde{Q}^f_{i,k})^{\frac{1}{\theta_1-1}}(L^f_i)^{-\frac{1}{\theta_1-1}} \tag{C.12}
$$

Using equation (C.11), and $v^f_{i,k\tau} = \widetilde{h}_{i,k\tau}a^f_{i,k\tau}(\gamma^L_{k\tau})^{-1}$,

$$
Q^f_{i,k\tau} = (\mu^f_{i,k})^{-(\theta_2-1)}(\gamma^L_{k\tau})^{-1}(p_{i,k})^{\theta_2-1}(a^f_{i,k\tau}\widetilde{h}_{i,k\tau})^{\theta_2}\widetilde{Q}^f_{i,k}
$$

or, equivalently,

$$
\frac{Q^f_{i,k\tau}}{v^f_{i,k\tau}} = (\mu^f_{i,k})^{-(\theta_2-1)}(p_{i,k})^{\theta_2-1}(a^f_{i,k\tau}\widetilde{h}_{i,k\tau})^{\theta_2-1}\widetilde{Q}^f_{i,k}. \tag{C.13}
$$

Recall the definition of $H^f_{i,k}$ from equation (5),

$$
H^f_{i,k} = \left[\sum_\tau(a^f_{i,k\tau}p_{i,k}\widetilde{h}_{i,k\tau})^{\theta_2}\right]^{\frac{1}{\theta_2}}.
$$

Using equation (C.13),

$$\underbrace{\Big[\sum_{\tau}\Big(\frac{Q^f_{i,k\tau}}{v^f_{i,k\tau}}\Big)^{\frac{\theta_2}{\theta_2-1}}\Big]^{\frac{\theta_2-1}{\theta_2}}}_{\widetilde{Q}^f_{i,k}} \quad = \quad (\mu^f_{i,k})^{-(\theta_2-1)}\widetilde{Q}^f_{i,k}(H^f_{i,k})^{\theta_2-1},$$

which delivers the shadow price of crop k, $\mu^f_{i,k}$, that is precisely equal to $H^f_{i,k}$,

$$\mu^f_{i,k} = H^f_{i,k}. \tag{C.14}$$

Let us now reproduce equation (C.12),

$$\widetilde{Q}^f_{i,k} = (\mu^f_{i,k})^{\theta_1-1}(\mu^f_i)^{-(\theta_1-1)}L^f_i. \tag{C.15}$$

which we use to derive the following relationship:

$$\underbrace{\Big[\sum_k(\widetilde{Q}^f_{i,k})^{\frac{\theta_1}{\theta_1-1}}\Big]^{\frac{\theta_1-1}{\theta_1}}}_{L^f_i} = (\mu^f_i)^{-(\theta_1-1)}L^f_i\Big[\sum_k(\mu^f_{i,k})^{\theta_1}\Big]^{\frac{\theta_1-1}{\theta_1}}.$$

Replacing $\mu^f_{i,k} = H^f_{i,k}$ from equation (C.14), we find the shadow price of total cropland, μ^f_i,

$$\mu^f_i = \Big[\sum_k(H^f_{i,k})^{\theta_1}\Big]^{\frac{1}{\theta_1}}. \tag{C.16}$$

Plug μ^f_i from (C.16) into (C.15),

$$\widetilde{Q}^f_{i,k} = (\mu^f_{i,k})^{\theta_1-1}\Big[\sum_k(\mu^f_{i,k})^{\theta_1}\Big]^{-\frac{\theta_1-1}{\theta_1}}L^f_i = \left[\frac{(H^f_{i,k})^{\theta_1}}{\sum_k(H^f_{i,k})^{\theta_1}}\right]^{\frac{\theta_1-1}{\theta_1}}L^f_i.$$

Replacing the above equation and equation (C.14) into equation (C.13), using $v^f_{i,k\tau} = (\gamma^L_{k\tau})^{-1}\widetilde{h}_{i,k\tau}a^f_{i,k\tau}$, we have:

$$Q^f_{i,k\tau} = (\gamma^L_{k\tau})^{-1}a^f_{i,k\tau}\widetilde{h}_{i,k\tau}\left[\frac{(a^f_{i,k\tau}\widetilde{h}_{i,k\tau})^{\theta_2}}{(H^f_{i,k})^{\theta_2}}\right]^{\frac{\theta_2-1}{\theta_2}}\left[\frac{(H^f_{i,k})^{\theta_1}}{\sum_k(H^f_{i,k})^{\theta_1}}\right]^{\frac{\theta_1-1}{\theta_1}}L^f_i.$$

This derivation reproduces equation (8) in the main text.

C.6 Derivations for the Gains from Trade

To highlight the main channels that drive the gains from trade, we simplify our model along two dimensions. First, suppose demand is a Cobb-Douglas combination between nonagriculture and agriculture that in turn consists of multiple crops:

$$C_i = (C^0_i)^{\beta^0_i}\left(\prod_k C^{\beta_{i,k}}_{i,k}\right)^{\beta^1_i},$$

where β_i^0 and $\beta_i^1 = 1 - \beta_i^0$ are the share of expenditure on nonagriculture and agriculture, and $\beta_{i,k}$ is the share of expenditure on crop k within agriculture. This means that compared to our main model, $\{\beta_i^0, \beta_i^1, \beta_{i,k}\}$ are exogenously fixed. Indirect utility is then given by:

$$C_i = \frac{Y_i}{(P_i^0)^{\beta_i^0} (\prod_k P_{i,k}^{\beta_{i,k}})^{\beta_i^1}}. \tag{C.17}$$

Second, on the production side, we make the assumption that agriculture does not use labor. As such, let traditional technology use only land ($\gamma_{k0}^L = 1$), and modern technology use land and intermediate inputs ($\gamma_{k1}^L + \gamma_{M1}^L = 1$). Value added generated by production of crop k in field f is then given by

$$V_{i,k}^f = p_{i,k} Q_{i,k0}^f + (1 - \gamma_{1,k}^M) p_{i,k} Q_{i,k1}^f.$$

Consider the equations that describe field-level crop quantities and relative land shares between the two technologies,

$$\begin{aligned} Q_{i,k\tau}^f &= L_i^f \left(\gamma_{k\tau}^L\right)^{-1} \left(\frac{m_{i,k}}{p_{i,k}}\right)^{-\frac{\gamma_{k,\tau}^M}{\gamma_{k,\tau}^L}} a_{i,k\tau}^f \left(\alpha_{i,k}^f\right)^{\frac{\theta_1 - 1}{\theta_1}} \left(\alpha_{i,k\tau}^f\right)^{\frac{\theta_2 - 1}{\theta_2}}, \\ \frac{\alpha_{i,k1}^f}{\alpha_{i,k0}^f} &= \left[\left(\frac{a_{i,k1}^f}{a_{i,k0}^f}\right) \left(\left(\frac{m_{i,k}}{p_{i,k}}\right)^{-\frac{\gamma_{k,1}^M}{\gamma_{k,1}^L}}\right)\right]^{\theta_2}. \end{aligned}$$

Combining these two equations, we obtain relative output quantities between the two technologies:

$$\frac{Q_{i,k1}^f}{Q_{i,k0}^f} = \left(\frac{\gamma_{k1}^L}{\gamma_{k0}^L}\right)^{-1} \left(\frac{\alpha_{i,k1}^f}{\alpha_{i,k0}^f}\right).$$

Replacing this into the expression for field-crop-specific value added, and noting that $\gamma_{k0}^L = 1$,

$$V_{i,k}^f = p_{i,k} L_i^f a_{i,k0}^f (\alpha_{i,k}^f)^{\frac{\theta_1 - 1}{\theta_1}} (\alpha_{i,k0}^f)^{\frac{-1}{\theta_2}}. \tag{C.18}$$

By aggregation over fields, total value added from production of crop k equals:

$$V_{i,k} = p_{i,k} \sum_{f \in \mathcal{F}_i} L_i^f a_{i,k0}^f (\alpha_{i,k}^f)^{\frac{\theta_1 - 1}{\theta_1}} (\alpha_{i,k0}^f)^{\frac{-1}{\theta_2}}. \tag{C.19}$$

We denote the value added share of nonagriculture by $\rho_{i,0} \equiv \frac{w_i N_i}{Y_i}$ and of crop k by $\rho_{i,k} \equiv \frac{V_{i,k}}{Y_i}$. In addition, let the value added share of field f within crop k be $\rho_{i,k}^f \equiv \frac{V_{i,k}^f}{V_{i,k}}$.

Consider a shock to trade costs that moves the baseline equilibrium to a new one. For any generic variable x, let x' be its value in the new equilibrium, and $\hat{x} \equiv x'/x$. Given the matrix of trade cost changes, $\{\hat{d}_{ni,k}\}$, from equation (11) that describes trade shares, we obtain:

$$\hat{\lambda}_{ii,0} = \left(\frac{\hat{w}_i}{\hat{P}_i^0}\right)^{1-\sigma_0}, \quad \hat{\lambda}_{ii,k} = \left(\frac{\hat{p}_{i,k}}{\hat{P}_{i,k}}\right)^{1-\sigma_k}. \tag{C.20}$$

From equations (C.18)-(C.19), and noting that $\hat{V}_{i,k} = \hat{\rho}_{i,k}\hat{Y}_i$,

$$\begin{aligned}
\hat{p}_{i,k} &= \hat{V}_{i,k}\left[\frac{\sum_f L_i^f a_{i,k0}^f (\hat{\alpha}_{i,k}^f \alpha_{i,k}^f)^{\frac{\theta_1-1}{\theta_1}} (\hat{\alpha}_{i,k0}^f \alpha_{i,k0}^f)^{\frac{-1}{\theta_2}}}{\sum_f L_i^f a_{i,k0}^f (\alpha_{i,k}^f)^{\frac{\theta_1-1}{\theta_1}} (\alpha_{i,k0}^f)^{\frac{-1}{\theta_2}}}\right]^{-1} \\
&= \hat{\rho}_{i,k}\hat{Y}_i\left[\sum_f \rho_{i,k}^f (\hat{\alpha}_{i,k}^f)^{\frac{\theta_1-1}{\theta_1}} (\hat{\alpha}_{i,k0}^f)^{\frac{-1}{\theta_2}}\right]^{-1}. \qquad (C.21)
\end{aligned}$$

Using equations (C.20)-(C.21) and noting that $\hat{w}_i = \hat{\rho}_{i,0}\hat{Y}_i$, we can express the change to price indexes of nonagriculture good and crops as:

$$\hat{P}_i^0 = \hat{\rho}_{i,0}\hat{Y}_i\left(\hat{\lambda}_{ii,0}\right)^{\frac{1}{\sigma_0-1}}, \quad \hat{P}_{i,k} = \hat{\rho}_{i,k}\hat{Y}_i\left[\sum_f \rho_{i,k}^f (\hat{\alpha}_{i,k}^f)^{\frac{\theta_1-1}{\theta_1}} (\hat{\alpha}_{i,k0}^f)^{\frac{-1}{\theta_2}}\right]^{-1}\left(\hat{\lambda}_{ii,k}\right)^{\frac{1}{\sigma_k-1}}. \qquad (C.22)$$

Replacing (C.22) into the hat-version of (C.17) reproduces equation (24) in the main text,

$$\hat{C}_i = \left(\hat{\rho}_{i,0}\left(\hat{\lambda}_{ii,0}\right)^{\frac{1}{\sigma_0-1}}\right)^{-\beta_i^0}\prod_k\left(\hat{\rho}_{i,k}\left(\hat{\lambda}_{ii,k}\right)^{\frac{1}{\sigma_k-1}}\right)^{-\beta_i^1\beta_{i,k}}\left[\sum_f \rho_{i,k}^f (\hat{\alpha}_{i,k}^f)^{\frac{\theta_1-1}{\theta_1}} (\hat{\alpha}_{i,k0}^f)^{\frac{-1}{\theta_2}}\right]^{\beta_i^1\beta_{i,k}}.$$

This reproduces equation (24) in the main text.

Now, suppose utility depends only on agriculture, i.e. $\beta_i^1 = 1$, $\beta_i^0 = 0$, and there is only one crop, i.e. $\alpha_{i,k}^f = \beta_{i,k} = \rho_{i,k} = 1$. Furthermore, suppose that in autarky, country i uses only traditional technology for production, and has access to domestic agricultural variety for consumption. Given these assumptions, and dropping subscript k to collapse the model to one-sector economy, the magnitude of the gains from trade, calculated as the loss of welfare from moving the baseline economy to autarky (labeled as A), equals:

$$G_i \equiv \frac{C_i - C_i^A}{C_i} = 1 - (\lambda_{ii})^{\frac{1}{\sigma-1}}\left[\sum_f \rho_i^f (\alpha_{i,0}^f)^{\frac{1}{\theta_2}}\right].$$

Replacing $\bar{\alpha}_{i,0} \equiv \left[\sum_f \rho_i^f (\alpha_{i,0}^f)^{\frac{1}{\theta_2}}\right]^{\theta_2}$, we can now reproduce equation (25) in the main text:

$$G_i = 1 - (\lambda_{ii})^{\frac{1}{\sigma-1}}(\bar{\alpha}_{i,0})^{\frac{1}{\theta_2}}.$$

D Details about the Estimation

This section presents details about the estimation of the model. Section D.1 starts by presenting additional discussion about the identification of the model. Section D.2 describes our bootstrap procedure.

D.1 Additional Discussion about Identification

In the main body of the paper, we used the following relationship coming from our model to derive expression 29:

$$\left(\frac{\alpha_{i,k1}}{\alpha_{i,k0}}\right) = \left[\frac{a_{i,k1}}{a_{i,k0}} \times \frac{(w_i/p_{i,k})^{-\gamma_{k1}^N/\gamma_{k1}^L}(m_{i,k}/p_{i,k})^{-\gamma_{k1}^M/\gamma_{k1}^L}}{(w_i/p_{i,k})^{-\gamma_{k0}^N/\gamma_{k0}^L}(m_{i,k}/p_{i,k})^{-\gamma_{k0}^M/\gamma_{k0}^L}}\right]^{\theta_2}.$$

We argued that (1) factor shares, γ-parameters, and θ_2 control how prices and relative productivities translate into relative land share of modern technology, (2) relative land share of modern technology is closely associated with the input cost share and input quantities per unit of land, which we target in our estimation. Using a pared-down version of our model, we now show how these two sets of variables are tightly related to relative land share of modern technology. In particular, we assume that countries produce using a single crop and have a single field.

We start by deriving the expression for the input cost share. Let C_i^{ag} be total expenditure in inputs in agriculture, R_i be total revenues in agriculture, R_{i0} and R_{i1} be revenues, respectively, in traditional and modern sector in agriculture, and γ_1^M be the cost share of inputs. Therefore, $\frac{C_i^{ag}}{R_i^{ag}} = \frac{\gamma_1^M R_{i1}}{R_{i1}+R_{i0}}$,which can be written as:

$$\frac{C_i^{ag}}{R_i^{ag}} \equiv \frac{\gamma_1^M}{1 + R_{i0}/R_{i1}}. \tag{D.1}$$

We now show how R_{i0}/R_{i1} relates to the inverse of relative land share of modern technology, α_{i0}/α_{i1}. To establish the link, we invoke the relative payments to land between the two technologies, $\frac{r_i L_{i0}}{r_i L_{i1}} = \frac{\gamma_0^L R_{i0}}{\gamma_1^L R_{i1}}$, which implies:

$$\frac{R_{i0}}{R_{i1}} = \frac{1}{\tilde{\gamma}^L} \frac{\alpha_{i0}}{\alpha_{i1}} \tag{D.2}$$

where we defined $\tilde{\gamma}^L \equiv \gamma_0^L/\gamma_1^L$, which is a parameter we estimate in our model. The cost share of inputs can thus be written as

$$\frac{C_i^{ag}}{R_i^{ag}} \equiv \frac{\gamma_1^M}{1 + \left(\tilde{\gamma}^L \dfrac{\alpha_{i1}}{\alpha_{i0}}\right)^{-1}}. \tag{D.3}$$

This expression shows how the relative share of land used in modern technology, $\frac{\alpha_{i1}}{\alpha_{i0}}$, affects the cost share of inputs, $\frac{C_i^{ag}}{R_i^{ag}}$, and how $\tilde{\gamma}^L$ matters to that relationship In particular, controlling for γ_1^M, when $\tilde{\gamma}^L$ is larger, the same value of $\frac{\alpha_{i1}}{\alpha_{i0}}$ translates to a larger cost share of inputs.

We now discuss the relationship between input quantities per unit of land and relative land share of modern technology. For concreteness, consider fertilizer-per-land, which is given by $\frac{F_i}{L_i} = \frac{r_i}{P_{i,F}} \frac{\gamma_1^{F,M}\gamma_1^M R_{i1}}{(\gamma_1^L R_{i1}+\gamma_0^L R_{i0})}$. Combining this expression with equation (D.2),

$$\frac{F_i}{L_i} = \frac{r_i}{P_{i,F}} \frac{\gamma_1^{F,M}\gamma_1^M}{\left(\gamma_1^L + \gamma_0^L \dfrac{1}{\tilde{\gamma}^L}\dfrac{\alpha_{i0}}{\alpha_{i1}}\right)}. \tag{D.4}$$

Given that $\tilde{\gamma}^L \equiv \gamma_0^L/\gamma_1^L$, and $\alpha_{i0} = 1 - \alpha_{i1}$,we can rearrange the above expression to obtain:

$$\frac{F_i}{L_i} = \frac{r_i}{P_{i,F}} \frac{\tilde{\gamma}^L}{\gamma_0^L} \gamma_1^{F,M} \gamma_1^M \alpha_{i1}. \tag{D.5}$$

Note that within the estimation of the model, we solve for equilibrium values of rents r_i, prices $P_{i,F}$, and land shares α_{i1}. The degree to which these variables influence F_i/L_i is partly governed by $\tilde{\gamma}^L$.

Lastly, we discuss about yields (land productivities). While shifters of land productivity, $a_{i,k\tau}^f$, are exogenous, land productivities in equilibrium —that is, conditional on the optimal selections of agricultural producers— are endogenous to local market conditions. Using equations (2) and (8), equilibrium yield of crop-technology pair (k, τ) in field f equals:

$$\frac{Q^f_{i,k\tau}}{L^f_{i,k\tau}} = (\gamma^L_{k\tau})^{-1}\tilde{h}_{i,k\tau}a^f_{i,k\tau}(\alpha^f_{i,k})^{-\frac{1}{\theta_1}}(\alpha^f_{i,k\tau})^{-\frac{1}{\theta_2}} \tag{D.6}$$

First, we note that the land intensity parameter operates as a scalar of equilibrium yields. Intuitively, a lower land intensity means higher intensity of non-land factors, hence a tendency for a higher land productivity. Using equation (3), this can be seen most clearly in the modern-to-traditional ratio of yields for the same crop in the same field,

$$\left(\frac{Q^f_{i,k1}}{L^f_{i,k1}}\right) \Big/ \left(\frac{Q^f_{i,k0}}{L^f_{i,k0}}\right) = \left(\frac{\gamma^L_{k,1}}{\gamma^L_{k,0}}\right)^{-1} = \tilde{\gamma}^L$$

When comparing yields across countries, local market conditions and productivity shifters in those countries would matter. However, controlling for them, a larger $\tilde{\gamma}^L$ implies a larger gap between average equilibrium yields in countries that intensively use modern technologies relative to those that intensively use traditional technology.

D.2 Bootstrap

We compute standard errors of our structural estimation based on "parametric bootstrap" (Horowitz, 2001). Our procedure works as follows. We assume that deviations between our model predictions and data arise from measurement errors. For any country-level variable v, we specify: $y_i^{v,data} = y_i^v(\Omega, \mathbf{X}) + \epsilon_i^v$ where $y_i^{v,data}$ is the log of our observation of variable v for country i, y_i^v is its counterpart predicted by the model at the vector of parameters Ω and data $\mathbf{X}$, and ϵ_i^v is an error term. By our specification, ϵ_i^v is distributed according to a normal distribution $N(0, \Lambda^v)$, and it is independent between countries and variables.

For our indirect inference, we construct aggregate statistics $\mathbf{m}^{data}$ from data points $\mathbf{y}^{data} \equiv \{y_i^{v,data}\}$. In the estimation, we minimize the distance between statistics $\mathbf{m}(\Omega, \mathbf{X})$ predicted by the model and their counterparts in the data, $\mathbf{m}^{data}$. In particular, country-level variables which we use to construct our statistics are: $v = \{$agricultural expenditure on intermediate inputs, agricultural gross output, quantity of fertilizer use, agricultural labor employment, crop-specific land use$\}$. Using our estimates of the model at $\widehat{\Omega}$, we compute predicted residuals: $\widehat{\epsilon}_i^v = y_i^{data,v} - \widehat{y}^v$. Using $\widehat{\boldsymbol{\epsilon}} \equiv \{\widehat{\epsilon}_i^v\}$, we estimate the empirical counterpart of the variance, $\widehat{\Lambda^v}$. We then draw the error terms, $\epsilon_i^{v,l}$ from $N(0, \widehat{\Lambda^v})$, where $l = 1, ..., L$ indexes the l-th set of simulated data. Using this procedure, we create a new set of model-generated data points: $y_i^{v,l} = \widehat{y}_i^v + \epsilon_i^{v,l}$. We call the l-th set of simulated data as $\mathbf{y}^l \equiv \{y_i^{v,l}\}$. For each simulated data set $\mathbf{y}^l$, we repeat our estimation algorithm in its entirety, and obtain estimates of $\widehat{\Omega}^l$. Lastly, we calculate confidence intervals and standard errors based on the distribution of $\{\widehat{\Omega}^l\}_{l=1}^L$.

E Details about the Counterfactual Simulations

This section describes how we measure changes in trade cost and productivity between 1980 and 2007 across countries, which we use in our counterfactual simulations. Section E.1 first describes how we measure changes in trade cost. Section E.2 then explains how we measure changes in productivity.

E.1 Measuring changes in trade costs

The method that we apply to measure changes in trade cost follow closely the literature using gravity trade models (see Head and Mayer (2014) for a detailed description of such methods). In particular, we assume that the trade costs that compose the residuals introduced in Section 5.1 ($b_{ni,g}d_{ni,g}^{1-\sigma_k}$) include a symmetric trade cost component, which we denote by $d_{ni,g}$. As such, one can easily use the demand equations from our model to write:

$$\log\left(\frac{X_{in,g}}{X_{ii,g}} \times \frac{X_{in,g}}{X_{nn,g}}\right) = \underbrace{2(1-\sigma_g)\log(d_{ni,g})}_{\delta_{in,g}} + \epsilon_{in,g}$$

where $\epsilon_{in,g} = \log(b_{ni,g}b_{in,g}/b_{ii,g}b_{ni,g})$. Since the values of $\delta_{in,g}$ are relative to a baseline group, we adopt the common approach in the literature and assume that $d_{ni,g} = 1$, which sets $\delta_{ii,g} = 0$. Using this assumption, we recover the fixed effects $\delta_{in,g}$, we then use our values of σ_g to recover $d_{ni,g}$.

Notice that, to recover the trade costs using the expression above, we need to measure the sales of a country to itself $X_{ii,g}$, which requires data on gross output. Unfortunately, data for gross output disaggregated by category of agricultural input or by crop is not available for 1980. To circumvent this limitation, we estimate trade costs using data for more aggregate sectors, agriculture and non-agriculture and, in our counterfactuals, we apply the changes in trade costs in non-agriculture to simulate the effects of globalization for agricultural inputs. To validate this approach, we use data for 2007 to compare the trade costs that we obtain for the aggregate of agricultural inputs (pesticides, machinery and fertilizers) and for the aggregate of non-agriculture. The correlation between these two measures of trade costs is high ($\rho = 0.75$), indicating that trade costs in non-agriculture serves as a good *proxy* for trade costs in agricultural inputs.

Figure A.7 shows percentage changes to trade costs between 1980 and 2007 for agricultural outputs and inputs, aggregated by regions. We find an average reduction of trade costs of 39% for outputs and by 41% for inputs. The fall in trade costs of agricultural inputs is typically larger than that of agricultural output. For both cases changes to trade costs are substantially heterogeneous across regions.

E.2 Measuring changes in productivity

In Section 5.1 in the main body of the paper, we estimated productivities using the gravity structure of our model. In particular, controlling for value added per worker, we recovered productivities from the origin fixed effects of regressions in which we use consumption shares as the dependent variable. We use the same procedure to measure relative productivities for agricultural machinery and pesticides in 1980. Similar to the limitation that we have in the case of trade cost, the lack of data on gross output for agricultural machinery and pesticide in 1980 prevents us from estimating relative productivities in 1980. We therefore use data on changes in productivity in non-agriculture between 1980 and 2007 as a *proxy* for the changes in productivity in machinery and pesticide. The correlation between productivity in non-agriculture in 2007 and the productivity of agricultural inputs as a whole is 0.98, which indicates that productivity in non-agriculture serves as a good *proxy* for productivity in agricultural inputs. Finally, to pin down the level of productivities so that we can compare 1980 with 2007, we bring in data from GGDC Productivity Level Database on the productivity of the US in tradeable goods (Inklaar and Timmer, 2008).

F Numerical Algorithms

This Section describes in detail the algorithms that we use to simulate and calibrate our model. Section F.1 starts by presenting the algorithm which we use to simulate the model. Section F.2 presents the calibration algorithm (i.e. inner problem) which we use in the structural estimation of our model.

F.1 Simulation of Model Equilibrium

Our solution algorithm takes endowments $\mathcal{E} \equiv \{L_n^f, N_n, V_n\}$, supply parameters $\Omega_S \equiv \{\theta_1, \theta_2, \gamma_{k\tau}^L, \gamma_{k\tau}^M, \gamma_{k\tau}^N, \gamma_k^{j,M}, a_{n,0}^f, a_{n,k\tau}^f\}$, and demand parameters $\Omega_D \equiv \{\varepsilon^0, \varepsilon^1, \eta, \kappa, \sigma_g, b_n^s, b_{n,k}, b_{ni,g}, d_{ni,g}, A_{n,g}\}$ as given, and solves for the vector of equilibrium prices.

1. Guess the vector wages $\{w_i\}_{i\in\mathcal{N}}$, crop prices $\{p_{i,k}\}_{i\in\mathcal{N},k\in\mathcal{K}}$, and fertilizer prices $\{p_{i,fert}\}_{n\in\mathcal{N}}$.

2. Calculate prices of nonagriculture, pesticides, agricultural machinery according to $p_{i,0} = w_i/A_{i,0}$, $p_{i,pest} = w_i/A_{i,pest}$ and $p_{i,mach} = w_i/A_{i,mach}$. (All these prices, $\{p_{i,g}\}$, are at the location of supply.)

3. For every good g (every of the crops, nonagriculture, fertilizer, pesticide, and agricultural machinery), calculate the price index at the location of consumption, $P_{n,g}$, according to equation (15), and expenditure (trade) share of every destination country n on every origin country i, $\lambda_{ni,g}$, according to equation (11).

4. (a) Compute the price index of agriculture, P_n^1, according to equation (15), and expenditure share on crops, $\beta_{n,k}$, according to (12). (b) Price index of sector-level nonagriculture bundle is $P_n^0 = P_{n,0}$. (c) Compute the aggregate price of intermediate inputs, $m_{n,k}$, according to $m_{n,k} = \prod_{j\in\mathcal{J}}(P_{n,j})^{\gamma_k^{j,M}}$.

5. (a) Calculate $h_{n,k\tau}$ and $\tilde{h}_{n,k\tau}$ according to (1). (b) Calculate $H_{n,k}^f$ according to (5).

6. Calculate land shares of crops, $\alpha_{n,k}^f$, and of technologies within every crop, $\alpha_{n,k\tau}^f$, based on equations (3)-(4).

7. (a) Compute production quantities at the level of field, $Q_{n,k\tau}^f$, based on (8), and at the level of country, $Q_{n,k}$, based on (9). (b) Compute aggregate quantity of investment, S_n, according to (10).

8. Calculate labor employment in agriculture, N_n^1, based on (20). Labor employment elsewhere is $N_{n,rest} = N_n - N_n^1$.

9. Calculate revenues generated from every of the crops, fertilizers, and the "rest" of the economy (pesticides, agricultural machinery, and nonagriculture), that are:

$$Y_{n,k} = p_{n,k}Q_{n,k}, \qquad Y_{n,fert} = p_{n,fert}V_n, \qquad Y_{n,rest} = w_nN_{n,rest}$$

10. Calculate total expenditure in every country n, E_n, according to equation (21).

11. Compute aggregate final consumption, C_n, and its corresponding price index, P_n, according to:
    (a) Guess C_n.
    (b) Calculate P_n according to (16).
    (c) Calculate: $C_n^{new} = E_n/P_n$. If $\max|(C_n^{new} - C_n)/C_n| < \epsilon$ for a sufficiently small tolerance ϵ, convergence is achieved. Otherwise, update $C_n = C_n^{new}$ and return to Step (b).

12. Calculate β_n^s based on (13).

13. Calculate global demand for every good based on equations (17)-(18)-(19),

$$X_{n,0} = \sum_{\ell}\beta_\ell^0\lambda_{\ell n,0}E_\ell, \qquad X_{n,j} = \sum_{\ell\in\mathcal{N}}\sum_{k\in\mathcal{K}}\gamma_k^{j,M}\gamma_{k1}^M\lambda_{\ell n,j}p_{\ell,k}Q_{\ell,k1}, \qquad X_{n,k} = \sum_{\ell}\beta_\ell^1\beta_{\ell,k}\lambda_{\ell n,0}E_\ell$$

    Let $X_{n,rest} = X_{n,0} + \sum_{j\in pest,mach} X_{n,j}$.

14. Update prices.

$$w_n^{new} = w_n \left(\frac{X_{n,rest}}{Y_{n,rest}}\right)^{\rho} \qquad p_{n,fert}^{new} = p_{n,fert} \left(\frac{X_{n,fert}}{Y_{n,fert}}\right)^{\rho} \qquad p_{n,k}^{new} = p_{n,k} \left(\frac{X_{n,k}}{Y_{n,k}}\right)^{\rho}$$

where $\rho \in (0,1)$ is a dampening parameter. If $\max|(X_{n,rest}-Y_{n,rest})/Y_{n,rest}| < \epsilon$, $\max|(X_{n,fert}-Y_{n,fert})/Y_{n,fert}| < \epsilon$, $\max|(X_{n,k}-Y_{n,k})/Y_{n,k}| < \epsilon$ for a sufficiently small tolerance ϵ, then convergence is achieved. Otherwise, update prices: $w_n = w_n^{new}$, $p_{n,fert} = p_{n,fert}^{new}$, $p_{n,k} = p_{n,k}^{new}$ and return to Step (2).

F.2 Calibration Algorithm

The calibration algorithm is the inner problem of our estimation procedure, which we represent by $c(\Gamma, \Theta) = 0$. Our calibration algorithm takes estimation parameters, $\Theta = \{\theta_1, \theta_2, \tilde{\gamma}\}$, data and calibration targets, $\mathbf{X}^{data} = \{y_{i,k\tau}^{f,data}, \alpha_{i,0}^{f,data}, Q_{USA,k}^{data}, \tilde{\alpha}_{USA,k}^{data}, \gamma_{USA}^{L,data}, \gamma_{USA}^{N,data}, \gamma_{USA}^{M,data}, \mu^{Fert}, \mu^{Pest}, \mu^{Mach}, N_i^{0,data}, E_i^{0,data}, E_i^{1,data}, L_i^{f,data}, V_i^{data}, \bar{\alpha}_{USA,k1}^{data}\}$, and demand-side parameters $\Omega_D \equiv \{\varepsilon^0, \varepsilon^1, \eta, \kappa, \sigma_g, b_n^s, b_{n,k}, b_{ni,g}, d_{ni,}$ as given, and solves for the vector of equilibrium prices and calibration parameters $\Gamma = \{\gamma_{k\tau}^L, \gamma_{k\tau}^M, \gamma_{k\tau}^N, a_{i,0}^f, a_{i,k\tau}^f\}$ such that equilibrium relationships of the model hold. Some of the steps in achieving this calibration are similar to the solution algorithm to the model equilibrium as explained in Section F.1, which we repeat here for the sake of completeness. We start with some preliminaries, then present our calibration algorithm.

Preliminaries for Calibration. For a clearer presentation, let us first spell out $\Gamma = \{\gamma_{k\tau}^L, \gamma_{k\tau}^M, \gamma_{k\tau}^N, a_{i,0}^f, a_{i,k\tau}^f\}$. Equation (27), i.e. $a_{i,k\tau}^f = \delta_{k\tau} y_{i,k\tau}^{f,data}$, is meant to help us connect land productivity shifters in our model, $\{a_{i,k\tau}^f\}$, to FAO-GAEZ data on potential yields, $\{y_{i,k\tau}^{f,data}\}$, by calibrating scale parameters $\{\delta_{k\tau}\}$. Specifically, we adjust the common scale of δ_{k0} and δ_{k1} such that predicted amount of production from our model matches that of data at the aggregate of the US, and we adjust the ratio of δ_{k1}/δ_{k0} such that predicted land share of modern technology from our model matches that of data at the aggregate of the US. In addition, we calibrate the shifter of total share of cropland (i.e. investment parameter for setting up agricultural production), $\{a_{i,0}^f\}$, according to equation (28). Lastly, we calibrate factor-intensity parameters $\{\gamma_{k\tau}^L, \gamma_{k\tau}^M, \gamma_{k\tau}^N\}$.

As explained in the main text, we assume common intensity parameters across crops, $\gamma_{k\tau}^L = \gamma_\tau^L$, $\gamma_{k\tau}^M = \gamma_\tau^M$, $\gamma_{k\tau}^N = \gamma_\tau^N$ and across input categories within intermediate inputs, $\gamma_k^{j,M} = \gamma^{j,M}$. We set the share of j = {Fertilizers (Fert), Pesticides (Pest), Agricultural Machinery (Mach)} according to the USDA Commodity Costs and Returns. In these data, there is a separate entry for "fertilizers" which we count as $j = Fert$. We count "Chemicals" as $j = Pest$, and the sum of "Capital recovery of machinery and equipment", "Interest on operating capital" and "Repairs" as $j = Mach$. Since these data are reported in dollars per unit of land, we aggregate them using data on land use in the USA. The final sample for which we have data on both input costs and land use consists of corn, rice, soybean, and wheat (among our list of crops). Also, to avoid potential fluctuations in the annual data, we calculate a ten-year average between 2000 and 2010. These calculations amount to: $\gamma^{Fert,M} = 0.256$, $\gamma^{Pest,M} = 0.158$, and $\gamma^{Mach,M} = 0.585$.

In addition, we use data on the aggregate share of land, labor, and intermediate inputs in the United States, $\{\gamma_{USA}^{L,data}, \gamma_{USA}^{N,data}, \gamma_{USA}^{M,data}\}$. We obtain $\gamma_{USA}^{M,data} = 0.58$ based on our country-level data set. By structure, $\gamma_{USA}^{L,data} + \gamma_{USA}^{N,data} + \gamma_{USA}^{M,data} = 1$, so we only need to know the aggregate labor-to-land cost ratio in the US. This ratio equals 1.38 according to the USDA TFP estimates for 2001-2010, while we find it to be less than 0.5 according to the USDA Commodity Costs and Returns.[33] Taking these

[33] As for the USDA TFP estimates and the methodology that is used there, see Fuglie (2012). As for the USDA Commodity Costs and Returns, we count "Opportunity cost of land" as Land, and we count sum of

values as bounds on the labor-to-land cost ratio in the US, we follow a simple rule of setting the ratio to one, $\gamma_{USA}^{N,data}/\gamma_{USA}^{L,data} = 1$, giving us: $\gamma_{USA}^{N,data} = 0.21$, $\gamma_{USA}^{L,data} = 0.21$, $\gamma_{USA}^{M,data} = 0.58$.

To connect these aggregate factor intensities to technology-specific factor intensity parameters, we note that any aggregate cost share is the weighted average between technology-specific cost shares. Specifically, let ω_{USA} be the aggregate output share of modern technology in the US. Then, our model implies:

$$\begin{cases} \gamma_{USA}^{L,data} = (1-\omega_{USA})\gamma_0^L + \omega_{USA}\gamma_1^L \\ \gamma_{USA}^{N,data} = (1-\omega_{USA})\gamma_0^N + \omega_{USA}\gamma_1^N \\ \gamma_{USA}^{M,data} = (1-\omega_{USA})\gamma_0^M + \omega_{USA}\gamma_1^M \end{cases} \tag{F.1}$$

Following the definitions of FAO-GAEZ, we set $\gamma_0^M = 0$. Note that labor shares are $\gamma_\tau^N = 1 - \gamma_\tau^L - \gamma_\tau^M$, because production features constant returns to scale at the level of plots. Hence, we only need to calibrate technology-specific land shares, (γ_0^L, γ_1^L). Since $\tilde{\gamma}^L \equiv \gamma_0^L/\gamma_1^L$ is given to us in the calibration (which is left to be estimated as explained in Section 5.2), and $\gamma_{USA}^{L,data} = (1-\omega_{USA})\gamma_0^L + \omega_{USA}\gamma_1^L$ (according to the above equation), we can pin down both γ_0^L and γ_1^L.

In the data which we use for calibration, $\mathbf{X}^{data}$, we denote by $\bar{\alpha}_{1,USA,k}^{data}$ the aggregate share of land under modern technology in the US. Due to data limitations, we assume that this share is common across crops, i.e. $\bar{\alpha}_{USA,k1}^{data} = \bar{\alpha}_{USA,1}^{data}$. For obtaining this share, we use information in a few sources. In the US Census of Agriculture, the area of land treated by "Commercial fertilizer, lime, and soil conditioners" is 94.5% relative to total land for crop production, and 78.7% relative to total agricultural land in 2012. Respecting figures are 108.9% and 85.9% in 2007. In addition, the area of land treated to "control weeds, grass, or brush" is 108.9% relative to total land for crop production and 90.6% relative to total agricultural land in 2012. Respecting figures are 92.7% and 73.1% in 2007. In addition, we examine information provided by the USDA Agricultural Chemical Use Program. According to US averages in 2010 (or the nearest year if 2010 is missing), the percent of acreage receiving nitrogen fertilizers is 97%, 90%, 27%, 86%, and 99% for corn, cotton, soybean, wheat (durum), and fall potato. The corresponding figures for herbicides are 98%, 99%, 98%, approximately 100%, and 94%. Based on these values, we follow a simple rule and set $\bar{\alpha}_{1,USA}^{data} = 0.95$.[34]

Calibration Algorithm. Given $\Theta = \{\theta_1, \theta_2, \tilde{\gamma}\}$, $\mathbf{X}^{data}$, Ω_D, the calibration algorithm solves for equilibrium prices and $\Gamma = \{\gamma_{k\tau}^L, \gamma_{k\tau}^M, \gamma_{k\tau}^N, a_{i,0}^f, a_{i,k\tau}^f\}$ as follows:

1. Guess $\delta_{k\tau}$, ω_{USA}, and $\{\gamma_{k\tau}^L, \gamma_{k\tau}^M, \gamma_{k\tau}^N\}$. (To be calibrated within the calibration steps below, along with equilibrium relationships of the model).

2. Using equation (27), set land productivity shifters:

$$a_{i,k\tau}^f = \delta_{k\tau} y_{i,k\tau}^{f,data}$$

"Hired labor" and "Opportunity cost of unpaid labor" as Labor. This gives a labor-to-land cost ratio of 0.37. Including "Custom services" or "Repairs" in the category of Labor slightly increases this ratio, but that remains below 0.50. Each of these two sources of labor-to-land cost ratio has its own limitations. For example, the USDA TFP estimates depend on a number of strong assumptions about agricultural production functions and compatibility of data across countries or over time, whereas in the USDA Commodity Costs and Returns, we are limited to a subset of crops as opposed to the entire crop production. In both of these sources, and potentially any other data source that reports labor employment in agriculture, there seems to be no authoritative practice for precisely which cost items should be attributable to labor.

[34]For these calculations, we are also careful to check the share of organic production in the US, and confirm that it is a very small portion of the US crop production circa 2010. According to the USDA, in 2011, only 3.1 million acres of cropland were certified organic, accounting for 1.18% of the share of land for crop production. For the top crops in the US, the share of organic production is negligible: 0.3 percent for corn, 0.2 percent for soybeans, and 0.6 percent for wheat.

3. Solve for equilibrium prices:

   (a) Guess the vector wages $\{w_i\}_{i\in\mathcal{N}}$, crop prices $\{p_{i,k}\}_{i\in\mathcal{N},k\in\mathcal{K}}$, and fertilizer prices $\{p_{i,fert}\}_{n\in\mathcal{N}}$.

   (b) Calculate prices of nonagriculture, pesticides, agricultural machinery according to $p_{i,0} = w_i/A_{i,0}$, $p_{i,pest} = w_i/A_{i,pest}$ and $p_{i,mach} = w_i/A_{i,mach}$. (All these prices, $\{p_{i,g}\}$, are at the location of supply.)

   (c) For every good g (every of the crops, nonagriculture, fertilizer, pesticide, and agricultural machinery), calculate the price index at the location of consumption, $P_{n,g}$, according to equation (15), and expenditure (trade) share of every destination country n on every origin country i, $\lambda_{ni,g}$, according to equation (11).

   (d) (a) Compute the price index of agriculture, P_n^1, according to equation (15), and expenditure shares on crops, $\beta_{n,k}$, according to (12). (b) Price index of sector-level nonagriculture bundle is $P_n^0 = P_{n,0}$. (c) Compute the aggregate price of intermediate inputs, $m_{n,k}$, according to $m_{n,k} = \prod_{j\in\mathcal{J}}(P_{n,j})^{\gamma_k^{j,M}}$.

   (e) (a) Calculate $h_{n,k\tau}$ and $\tilde{h}_{n,k\tau}$ according to (1). (b) Calculate $H_{n,k}^f$ according to (5).

   (f) Calculate land shares of technologies within every crop, $\alpha_{n,k\tau}^f$, based on equations (3).

   (g) Recover the investment parameter based on equation (28)

$$a_{i,0}^f = \frac{1}{P_i^0}\left(\sum_k (H_{i,k}^f)^{\theta_1}\right)^{\frac{1}{\theta_1}}\left(\frac{1-\alpha_{i,0}^{f,data}}{\alpha_{i,0}^{f,data}}\right)^{\frac{1}{\theta_1}}$$

   (h) Calculate land shares of crops, $\alpha_{n,k}^f$, based on equations (4).

   (i) (a) Compute production quantities at the level of field, $Q_{n,k\tau}^f$, based on (8), and at the level of country, $Q_{n,k}$, based on (9). (b) Compute aggregate quantity of investment, S_n, according to (10). In these calculations, $L_i^f = L_i^{f,data}$.

   (j) Calculate the model prediction of country-level land share of crops that use modern technology,

$$\bar{\alpha}_{n,k1} = \left(\sum_{f\in\mathcal{F}_n} L_n^f \alpha_{n,k}^f \alpha_{n,k1}^f\right) \Big/ \left(\sum_{f\in\mathcal{F}_n} L_n^f \alpha_{n,k}^f\right)$$

   (k) Calculate revenues generated from every of the crops, fertilizers, and the "rest" of the economy (pesticides, agricultural machinery, and nonagriculture), that are:

$$Y_{n,k} = p_{n,k}Q_{n,k}, \qquad Y_{n,fert} = p_{n,fert}V_n^{data}, \qquad Y_{n,rest} = w_n N_n^{0,data}$$

   (l) Calculate global demand for every good based on equations (17)-(18)-(19),

$$X_{n,0} = \sum_\ell \lambda_{\ell n,0}E_\ell^{0,data}, \qquad X_{n,j} = \sum_{\ell\in\mathcal{N}}\sum_{k\in\mathcal{K}} \gamma_k^{j,M}\gamma_{k1}^M \lambda_{\ell n,j} p_{\ell,k} Q_{\ell,k1}, \qquad X_{n,k} = \sum_\ell \beta_{\ell,k}\lambda_{\ell n,0}E_\ell^{1,data}$$

   Let $X_{n,rest} = X_{n,0} + \sum_{j\in pest,mach} X_{n,j}$.

   (m) Update prices:

$$w_n^{new} = w_n\left(\frac{X_{n,rest}}{Y_{n,rest}}\right)^\rho \qquad p_{n,fert}^{new} = p_{n,fert}\left(\frac{X_{n,fert}}{Y_{n,fert}}\right)^\rho \qquad p_{n,k}^{new} = p_{n,k}\left(\frac{X_{n,k}}{Y_{n,k}}\right)^\rho$$

where $\rho \in (0,1)$ is a dampening parameter. If $\max|(X_{n,rest}-Y_{n,rest})/Y_{n,rest}| < \epsilon$, $\max|(X_{n,fert}-Y_{n,fert})/Y_{n,fert}| < \epsilon$, $\max|(X_{n,k}-Y_{n,k})/Y_{n,k}| < \epsilon$ for a sufficiently small tolerance ϵ, then convergence is achieved. Otherwise, update prices: $w_n = w_n^{new}$, $p_{n,fert} = p_{n,fert}^{new}$, $p_{n,k} = p_{n,k}^{new}$ and return to Step (b).

4. Update $\delta_{k\tau}$, ω_{USA}, and $\{\gamma^L_{k\tau}, \gamma^M_{k\tau}, \gamma^N_{k\tau}\}$,

   (a) Update scale parameters that connect the shifters of land productivity in the model to the FAO-GAEZ potential yield data,

$$\delta_{k0}^{new} = \delta_{k0}\left(\frac{Q^{data}_{USA,k}}{Q_{USA,k}}\right)^{\rho}, \qquad \delta_{k1}^{new} = \delta_{k1}\left(\frac{\bar{\alpha}^{data}_{USA,k}}{\bar{\alpha}_{USA,k}}\right)^{\rho}$$

   (b) Update the share of production from modern technology in the US, $\omega^{new}_{USA} = \sum_k Q_{USA,k1}/\sum_k Q_{USA,k}$.

   (c) Update factor intensity parameters according to equation (F.1),

$$\begin{cases} \gamma_0^{L,new} = \frac{\gamma^{L,data}_{USA}}{(1-\omega_{USA})+\omega_{USA}/\tilde{\gamma}^L}, \quad \gamma_0^{N,new} = 1-\gamma_0^L, & \text{(traditional tech)} \\ \gamma_1^{L,new} = \gamma_0^L/\tilde{\gamma}^L, \quad \gamma_1^{M,new} = \gamma^{M,data}_{USA}/\omega_{USA}, \quad \gamma_1^{N,new} = 1-\gamma_1^M-\gamma_1^L, & \text{(modern tech)} \end{cases}$$

   where in part (a), $\rho \in (0,1)$ is a dampening parameter. If $|(Q^{data}_{USA,k} - Q_{USA,k})/Q^{data}_{USA,k}| < \epsilon$, $|(\bar{\alpha}^{data}_{USA,k} - \bar{\alpha}_{USA,k})/\bar{\alpha}^{data}_{USA,k}| < \epsilon$, $|(\omega^{new}_{USA} - \omega_{USA})| < \epsilon$ for a sufficiently small ϵ, then convergence is achieved. Otherwise, let $\delta^{new}_{k0} = \delta_{k0}$, $\delta^{new}_{k1} = \delta_{k1}$, $\omega^{new}_{USA} = \omega_{USA}$, $\gamma_0^L = \gamma_0^{L,new}$, $\gamma_0^N = \gamma_0^{N,new}$ (where, by structure, $\gamma_0^M = 0$), $\gamma_1^L = \gamma_1^{L,new}$, $\gamma_1^M = \gamma_1^{M,new}$, $\gamma_1^N = \gamma_1^{N,new}$, and return to Step (2).

G Additional Tables and Figures

G.1 Tables

G.1.1 Data Description

Table A.1: Summary Statistics for Selected Variables by Region

	North America (1)	East Asia (2)	East Europe (3)	Latin America (4)	MENA (5)	South Asia (6)	SSA (7)	West Europe (8)	World (9)
GDP per capita	1.00	0.14	0.15	0.14	0.09	0.03	0.02	0.76	0.17
VA per worker (ag)	0.68	0.06	0.03	0.04	0.03	0.01	0.01	0.29	0.02
Imp share of inputs	0.20	0.08	0.66	0.56	0.48	0.29	0.75	0.50	0.30
- Machinery	0.23	0.08	0.65	0.68	0.48	0.16	0.86	0.42	0.33
- Fertilizer	0.51	0.23	0.52	0.76	0.42	0.40	0.63	0.64	0.48
- Pesticide	0.10	0.05	0.78	0.35	0.69	0.20	0.85	0.55	0.20
Countries	2	5	6	12	6	9	12	13	66

Notes: This table reports aggregate values of selected variables for countries in each of the listed eight regions in the world. The reported variables are GDP per capita, value added per worker in agriculture, import share of agricultural inputs, as measured by a country's imports of inputs relative to total expenditure on them. East Asia includes countries in the Pacific region, MENA stands for Middle East and North African countries, and SSA for Sub-Saharan Africa.

G.1.2 Counterfactual Exercises

Table A.2: Impact of Changes in Trade Costs from the Baseline in 2007 to the Counterfactual Economy in 1980 by Quartile of GDP per capita in the Baseline (Percentual Change)

	Changes in Trade Costs in Agricultural											
	Output and Input				Only Input				Only Output			
	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q1 (5)	Q2 (6)	Q3 (7)	Q4 (8)	Q1 (9)	Q2 (10)	Q3 (11)	Q4 (12)
a. Domestic Expenditure Shares												
Ag input	8.2	17.5	57.3	12.6	8.5	20.7	57.6	12.8	-2.0	-3.4	-1.6	-1.2
Ag output	5.2	5.7	15.0	10.7	-0.3	-2.4	-2.8	0.9	6.1	8.2	17.4	10.0
b. Agricultural production												
Land modern	-3.4	-5.5	-6.2	-0.4	-3.0	-5.7	-10.3	-0.4	0.0	0.2	3.8	0.1
Yield	-5.1	-8.6	-13.3	-3.9	-2.6	-5.6	-11.9	-4.6	-2.0	-3.4	-1.1	1.1
Ag labor (%)	5.0	4.1	19.0	14.6	5.5	3.4	3.9	6.5	-0.7	0.5	11.9	8.0
c. Welfare												
Food cons	-2.5	-2.4	-8.0	-5.3	-1.6	-2.0	-4.2	-2.6	-1.0	-0.6	-3.4	-2.7
Welfare	-3.6	-3.1	-3.2	-1.4	-1.0	-1.3	-1.6	-0.6	-2.5	-1.6	-1.4	-0.8

Notes: This table shows results disaggregated by the quartiles of GDP per capita for our "globalization" counterfactuals in which we change trade costs to their levels in 1980. Every reported number is the unweighted average of percentage changes across countries within each quartile.

Table A.3: Impact of Changes in Trade Costs from the Baseline in 2007 to the Counterfactual Economy in 1980 (Percentage Change) - Same Trade Cost between Countries and between Agricultural Output and Input

	Changes in Trade Costs in Agriculture		
	Output and Input	Only Input	Only Output
	(1)	(2)	(3)
a. Domestic expenditure shares			
Agricultural input	30.3	34.0	-5.3
Agricultural output	17.3	-1.7	18.1
b. Agricultural production			
Share of land in modern	-6.8	-8.2	1.5
Yield (avg across crops)	-12.4	-10.3	-1.4
Agricultural labor share	9.6	7.3	1.2
c. Welfare			
Food consumption	-5.9	-3.7	-2.5
Welfare	-4.0	-1.7	-2.1
d. Inequality (Q4/Q1)			
Food consumption	-7.6	-3.0	-4.8
Welfare	2.4	0.0	2.1

Notes: This table re-generates results in Table 4 for a uniform reduction of trade costs (both across countries, and between agricultural outputs and inputs). Specifically, we apply a change of 44% reduction to all finite bilateral trade costs.

Table A.4: Impact of Reduction in Trade Costs from the Baseline in 2007 to the Counterfactual Economy in 1980 by Quartile of GDP per capita (Percentual Change) - Same Trade Cost between Countries and between Agricultural Output and Input

	Changes in Trade Costs in Agricultural											
	Output and Input				Only Input				Only Output			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
a. Domestic Expenditure Shares												
Ag input	12.9	30.9	63.2	24.9	14.7	36.1	68.2	26.2	-3.9	-5.7	-3.7	-4.3
Ag output	7.7	12.6	21.0	27.5	-0.2	-4.5	-1.0	1.9	8.9	14.5	23.2	26.0
b. Agricultural production												
Land modern	-8.0	-10.4	-8.0	-0.8	-7.4	-10.8	-12.4	-1.3	-0.6	0.2	4.3	0.5
Yield	-8.0	-15.1	-18.6	-6.0	-5.8	-8.4	-17.4	-9.2	-2.3	-5.2	-1.2	2.9
Ag labor (%)	6.2	7.6	24.8	32.8	9.0	4.9	8.5	11.4	-2.7	0.3	14.2	21.8
c. Welfare												
Food cons	-3.0	-3.7	-10.0	-10.4	-2.2	-2.9	-5.5	-5.2	-1.1	-0.8	-4.4	-5.8
Welfare	-5.4	-4.8	-4.5	-3.2	-1.4	-2.2	-2.2	-1.4	-3.8	-2.2	-2.1	-1.7

Notes: This table re-generates results in Table A.2 for a uniform reduction of trade costs (both across countries, and between agricultural outputs and inputs). Specifically, we apply a change of 44% reduction to all finite bilateral trade costs.

Table A.5: Effects of Changes in Productivity of Agricultural Inputs (part 1)

	Changes in							
	Prod (%)	Endow (%)	Land Modern (%)		Avg Yields		Labor in Ag	
Counterfactual	Pest-Mach	Fert	All	CbyC	All	CbyC	All	CbyC
Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ALB	1.65	0.57	-42.08	-13.34	-0.31	-0.11	64.20	0.85
ARG	2.31	6.15	-77.12	-23.96	-0.29	-0.09	72.92	4.68
AUS	2.63	2.06	-22.64	-10.17	-0.39	-0.20	53.81	-4.79
AUT	3.94	0.85	-20.92	-6.92	-0.41	-0.20	31.29	-19.76
BFA	1.88	5.53	-93.15	-25.94	-0.11	-0.00	51.13	0.08
BGD	2.75	3.18	-53.43	-15.02	-0.28	-0.15	70.41	-4.37
BRA	2.68	2.78	-55.97	-31.93	-0.45	-0.28	61.58	16.51
CAN	2.17	1.54	-10.02	-3.78	-0.39	-0.16	50.01	-11.97
CHL	6.61	4.48	-52.02	-7.04	-0.49	-0.09	47.63	-7.11
CHN	12.25	2.64	-73.09	-55.23	-0.73	-0.60	58.63	20.33
CIV	1.21	1.99	-31.69	-2.32	-0.18	-0.01	20.88	1.30
CMR	1.20	1.33	-25.29	-3.27	-0.15	-0.01	31.98	0.39
COG	0.71	0.55	21.32	24.63	-0.13	0.04	20.54	-1.44
COL	2.28	1.90	-35.00	-14.86	-0.51	-0.23	37.03	-1.10
CRI	3.32	1.94	-35.45	-3.65	-0.36	-0.05	52.31	0.85
CZE	5.78	0.53	-14.13	-1.03	-0.35	-0.05	38.49	-2.76
DEU	2.77	0.62	-1.37	-0.49	-0.30	-0.17	36.82	-17.77
DOM	1.82	1.95	-36.72	-2.34	-0.15	-0.02	52.26	2.17
DZA	0.71	1.27	-28.51	7.76	-0.17	0.03	40.37	-2.28
ECU	1.54	4.66	-53.18	-7.50	-0.28	-0.04	49.04	1.40
EGY	9.91	5.12	-12.69	-2.64	-0.52	-0.21	55.68	-13.68
ESP	4.01	1.29	-20.28	-4.08	-0.45	-0.22	20.59	-14.60
ETH	1.06	6.15	-55.54	-8.79	-0.17	-0.01	29.36	0.85
FIN	3.79	0.75	-3.12	-0.80	-0.40	-0.20	19.36	-26.28
FRA	2.19	0.65	-4.72	-0.96	-0.29	-0.10	38.54	-6.28
GBR	1.90	0.78	-1.45	-0.15	-0.26	-0.05	36.02	-2.53
GHA	1.96	3.08	-69.25	-10.27	-0.20	-0.03	58.95	2.62
GRC	2.58	0.76	-18.34	-5.52	-0.45	-0.21	30.85	-11.87
HUN	5.56	0.53	-32.34	-0.75	-0.19	-0.00	64.05	1.98
IDN	7.15	2.06	-44.32	-16.46	-0.44	-0.23	68.96	-4.44
IND	5.57	3.19	-42.21	-34.50	-0.55	-0.51	57.14	24.17
IRN	3.54	2.01	-48.87	-33.72	-0.45	-0.36	97.08	-13.73
ITA	2.95	0.65	-8.44	-4.60	-0.42	-0.37	22.55	-25.85

Notes: This table reports results by country for the counterfactuals in Section E.2 where we re-calibrate productivities of the agricultural input sector. The first two columns report the percentage change in the productivity of pesticides and farm machinery, and in the fertilizer production between the baseline of 2007 and 1980. These are exogenous changes which we feed into the simulation of the counterfactual equilibrium. Reported as values in the counterfactual with productivity parameters of 1980 relative to the baseline of 2007, the table reports land share of modern technology, average yields (across crops within each country), and agricultural labor employment for the case of "shocks to all countries" (All) and "shocks, country by country" (CbyC).

Table A.6: Effects of Changes in Productivity of Agricultural Inputs (part 2)

	Changes in							
	Prod (%)	Endow (%)	Land Modern (%)		Avg Yields		Labor in Ag	
Counterfactual	Pest-Mach	Fert	All	CbyC	All	CbyC	All	CbyC
Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
JPN	2.28	0.70	-1.62	-0.96	-0.33	-0.22	30.53	5.29
KEN	1.05	1.97	-46.94	-3.14	-0.24	-0.01	35.84	0.75
KOR	12.25	0.93	-2.80	-0.37	-0.48	-0.15	42.54	-3.39
LKA	6.22	1.89	-81.51	-16.97	-0.18	-0.05	142.56	-0.96
MAR	3.34	3.64	-66.80	-11.06	-0.23	-0.06	54.96	-2.29
MEX	3.11	1.21	-42.24	-6.99	-0.43	-0.08	42.22	-2.30
MLI	2.68	5.10	-86.58	-26.60	-0.14	0.00	51.67	0.57
MOZ	0.71	1.53	-38.40	3.85	-0.28	0.02	27.75	-1.14
MYS	6.20	3.43	-15.63	-1.12	-0.54	-0.10	39.76	-7.52
NLD	2.77	0.64	-0.13	-0.02	-0.29	-0.09	33.17	-9.53
NOR	4.67	1.42	-3.89	-0.57	-0.46	-0.12	17.90	-20.96
NZL	1.95	2.08	-27.80	-14.97	-0.34	-0.16	76.85	-9.44
PAK	2.64	2.48	-48.64	-27.15	-0.25	-0.18	65.87	-4.18
PER	3.00	3.11	-73.69	-22.49	-0.45	-0.14	64.92	-2.90
PHL	2.42	2.55	-58.50	-18.46	-0.21	-0.09	81.10	-0.07
POL	3.73	0.78	-17.62	-2.47	-0.37	-0.10	35.94	-4.04
PRT	4.67	1.39	-64.04	-13.28	-0.56	-0.17	39.72	-11.99
PRY	1.41	6.15	-34.81	-2.12	-0.40	-0.03	20.84	2.77
ROU	2.43	0.53	-22.13	-2.22	-0.31	-0.05	44.11	3.28
ROW	2.18	1.22	-32.64	-6.72	-0.40	-0.09	55.02	1.61
SEN	1.73	1.55	-79.66	-70.15	-0.21	-0.07	108.81	6.81
SOV	1.91	0.87	-29.99	-10.21	-0.33	-0.12	48.12	5.10
SWE	2.72	0.63	-4.36	-0.71	-0.36	-0.10	31.69	-12.78
THA	11.49	5.29	-28.46	-3.06	-0.48	-0.10	47.59	-2.82
TUN	5.11	1.93	-69.33	-10.51	-0.07	-0.03	49.86	-2.90
TUR	7.33	1.31	-36.46	-11.93	-0.57	-0.34	35.62	-7.07
TZA	1.33	3.34	-72.46	-2.51	-0.21	-0.00	40.91	0.51
URY	2.45	3.76	-75.30	-9.00	-0.32	-0.03	68.85	2.54
USA	1.77	0.95	-7.21	-5.93	-0.28	-0.19	36.25	-2.48
VEN	1.88	1.84	-24.09	-7.04	-0.39	-0.19	32.04	8.34
VNM	12.25	6.01	-50.00	-12.32	-0.29	-0.10	81.05	-4.76
YUG	0.72	0.92	0.35	7.97	-0.08	0.10	57.78	1.48
ZAF	2.36	0.88	-67.88	-5.75	-0.40	-0.04	76.25	3.15

Notes: This table is the second part of Table A.5.

Table A.7: Effects of Changes in Productivity of Agricultural Inputs - Effects on Welfare (part 1)

	Changes in					
	Welfare		Non-ag Consumption		Food Consumption	
Counterfactual	All	CbyC	All	CbyC	All	CbyC
Country	(1)	(2)	(3)	(4)	(5)	(6)
ALB	-32.93	-2.88	-29.68	-2.64	-15.23	-1.53
ARG	-0.59	-1.63	2.92	-2.44	-14.68	-3.36
AUS	-3.28	-2.45	-2.31	-3.62	-21.92	-7.67
AUT	-4.50	-1.28	-5.43	-2.31	-22.89	-2.02
BFA	13.58	-0.06	29.40	-0.09	-0.65	-0.06
BGD	-32.47	-6.61	-30.13	-8.35	-25.63	-4.58
BRA	-6.14	-4.58	-4.37	-5.26	-20.08	-11.06
CAN	-2.63	-2.47	-1.88	-4.40	-20.69	-3.84
CHL	-9.50	-2.23	-10.75	-3.74	-23.74	-2.58
CHN	-23.37	-16.18	-23.49	-17.84	-39.81	-29.19
CIV	5.47	-0.55	15.24	-0.79	-7.85	-0.75
CMR	7.57	-0.37	16.42	-0.52	-1.06	-0.39
COG	9.52	0.45	18.70	0.42	1.23	0.55
COL	-10.14	-5.38	-9.06	-6.82	-18.60	-7.41
CRI	-6.26	-1.33	-6.35	-2.19	-19.71	-1.85
CZE	-5.35	-0.01	-4.66	0.08	-21.55	-0.42
DEU	-2.32	-0.50	-1.37	-0.74	-21.52	-2.19
DOM	-4.43	-0.73	-2.51	-0.85	-17.17	-1.94
DZA	-0.03	0.24	3.14	0.01	-6.78	1.09
ECU	-5.75	-0.96	-2.48	-1.11	-13.84	-1.44
EGY	-36.96	-17.82	-41.22	-25.26	-33.61	-13.09
ESP	-6.08	-1.28	-6.20	-1.98	-23.10	-2.80
ETH	17.64	-1.38	38.75	-2.03	-0.41	-1.15
FIN	-3.11	-0.36	-2.50	-0.53	-22.07	-1.34
FRA	-2.87	-0.66	-0.99	-0.93	-19.47	-1.97
GBR	-1.59	-0.79	-0.03	-1.34	-19.64	-1.87
GHA	-2.88	-1.58	3.98	-1.98	-12.64	-1.81
GRC	-6.98	-1.34	-6.07	-1.78	-21.43	-3.00
HUN	-3.38	0.12	-1.72	0.29	-19.99	-0.22
IDN	-21.26	-6.45	-19.62	-7.80	-27.71	-7.84
IND	-26.15	-22.19	-25.11	-23.75	-34.68	-28.70
IRN	-23.36	-5.80	-22.07	-6.61	-31.10	-8.36
ITA	-5.91	-2.04	-5.96	-2.96	-23.00	-5.38

Notes: This table reports results by country for the counterfactuals in Section E.2 where we re-calibrate productivities of the agricultural input sector. Reported as values in the counterfactual with productivity parameters of 1980 relative to the baseline of 2007, the table reports percentage changes to welfare, consumption of non-agricultural (C_{i0}) and of food (C_{i1}).

Table A.8: Effects of Changes in Productivity of Agricultural Inputs - Effects on Welfare (part 2)

	Changes in					
	Welfare		Non-ag Consumption		Food Consumption	
Counterfactual	All	CbyC	All	CbyC	All	CbyC
Country	(1)	(2)	(3)	(4)	(5)	(6)
JPN	-3.30	-2.44	-2.51	-2.72	-20.55	-12.04
KEN	4.19	-1.49	14.23	-2.16	-5.42	-0.95
KOR	-7.15	-1.44	-7.44	-1.83	-28.50	-5.72
LKA	-28.14	-0.46	-25.74	-0.61	-23.66	-0.30
MAR	-21.93	-11.98	-23.73	-17.93	-25.03	-8.52
MEX	-5.62	-0.70	-5.09	-0.96	-18.39	-1.62
MLI	9.27	-1.67	20.14	-2.76	-1.12	-1.06
MOZ	19.06	0.33	42.35	0.37	-0.98	0.66
MYS	-7.62	-2.12	-7.85	-3.68	-26.44	-2.51
NLD	2.24	1.24	7.53	2.38	-17.89	0.83
NOR	-4.91	-1.31	-5.02	-2.29	-22.71	-1.93
NZL	-6.02	-1.97	-4.96	-3.17	-23.43	-3.19
PAK	-18.90	-5.44	-15.85	-6.39	-21.91	-5.45
PER	-7.67	-0.97	-6.29	-1.13	-18.95	-2.06
PHL	-15.38	-2.75	-12.88	-3.35	-22.01	-3.28
POL	-4.79	-0.39	-2.58	-0.27	-20.55	-1.86
PRT	-6.92	-0.74	-6.98	-1.23	-21.72	-1.00
PRY	-0.60	-1.15	5.74	-1.65	-13.77	-1.56
ROU	-5.20	2.39	1.53	4.69	-14.74	0.23
ROW	-12.58	-4.63	-7.58	-6.16	-18.10	-3.78
SEN	-11.45	-10.39	-8.87	-15.65	-18.31	-7.17
SOV	-10.81	-3.38	-7.12	-3.25	-14.95	-4.12
SWE	-3.98	-0.73	-3.81	-1.23	-22.31	-1.53
THA	-13.82	-1.96	-13.74	-2.81	-24.29	-2.49
TUN	-11.86	-8.41	-13.64	-13.97	-23.06	-6.91
TUR	-17.42	-5.80	-17.53	-7.14	-27.52	-8.91
TZA	23.65	-0.41	52.99	-0.58	-0.05	-0.19
URY	4.83	-0.82	13.48	-1.30	-11.57	-1.41
USA	-1.64	-2.20	0.53	-2.68	-16.27	-8.18
VEN	-5.93	-3.43	-5.43	-4.43	-18.54	-7.87
VNM	-24.50	-6.51	-24.35	-9.43	-27.84	-5.19
YUG	-0.24	1.78	8.89	2.35	-10.86	1.73
ZAF	-0.03	-0.49	3.70	-0.74	-16.82	-1.35

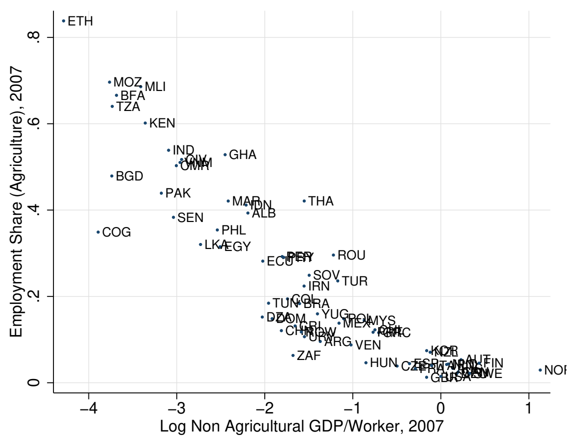
Notes: This table is the second part of Table A.7.

G.2 Figures

G.2.1 Data Description

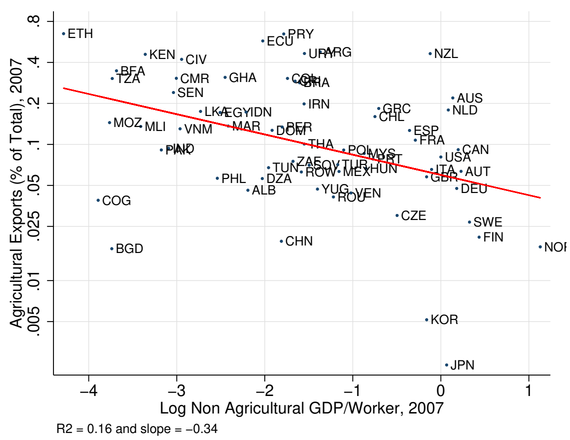
Figure A.1: Additional Cross-Country relationships between Agricultural Activity and GDP per capita

(a) Labor Share in Agriculture

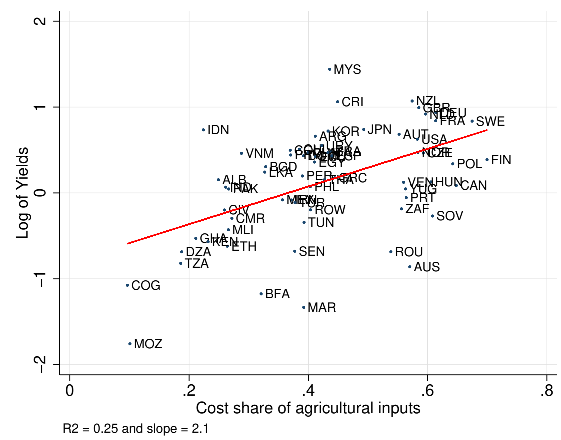


(b) Share of Expenditure in Agriculture

(c) Agricultural Exports (% of total)



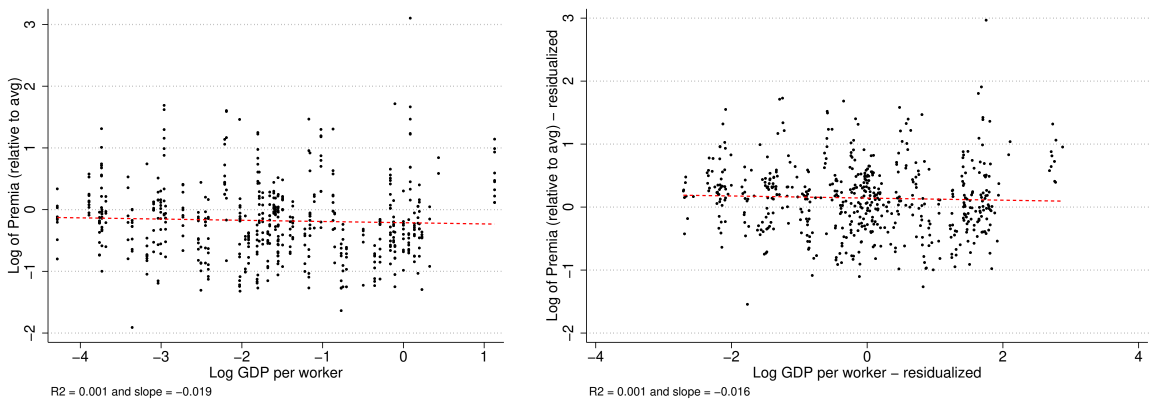
(d) Average Yields



Notes: Panels (a)-(b) plot the agriculture labor share and food expenditure share against GDP per capita. Panel (c) plots the share of agricultural exports in total exports of every country against its value added per worker in non-agriculture sector. We normalize GDP per capita of every country by that of the US. Panel (d) plots the data on average normalized yield against agricultural input cost share across countries, on the log scale. With $x_{i,k} = (Q_{i,k}/L_{i,k}) / (\sum_i (Q_{i,k}/L_{i,k})/N)$ as yield of crop k in country i normalized by the global average yield of crop k, "average normalized yield" of country i is defined as $x_i = L_{i,k}x_{i,k}/\sum_k L_{i,k}$.

Figure A.2: Modern Potential Yield Premia against GDP per capita

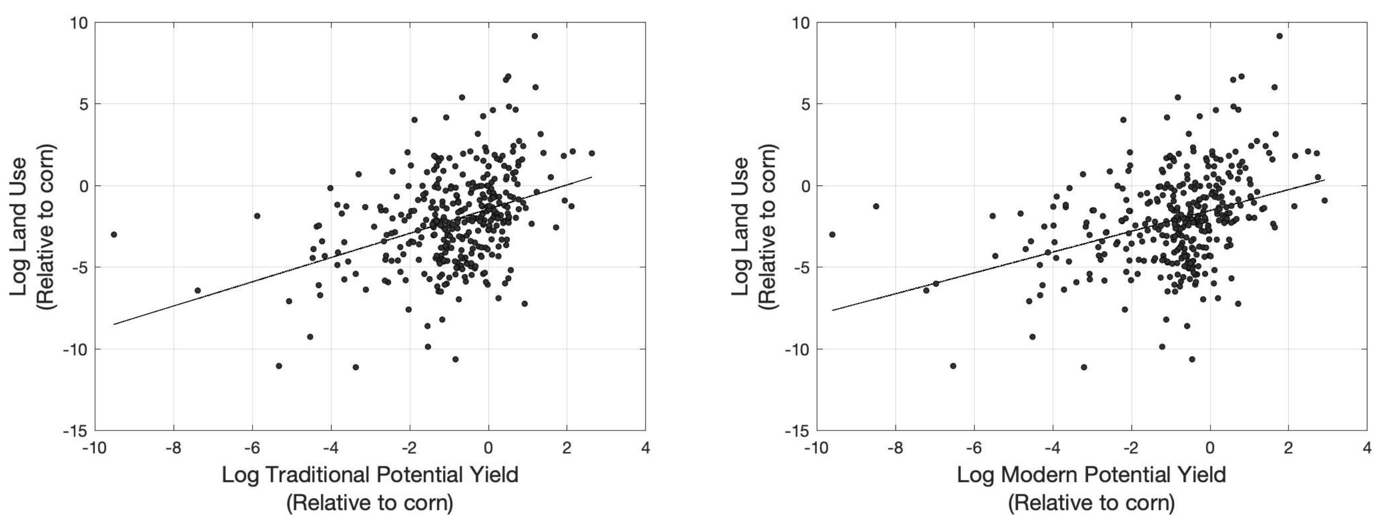
(a) Unconditional (b) Conditional on Potential Yield of Traditional



Notes: Each point in this figure represents a crop-country pair. In Panel (a) the y-axis is average modern potential yield premium across all fields within each country-crop cell, normalized by the global average premia of the corresponding crop. The x-axis is GDP per capita in 2007, normalized by the GDP per capita in the US. Panel (b) re-plots the relationship using residual premia conditional on potential premium of traditional technology. To do so, we first obtain the residuals of a regression of the modern potential yield premia against the potential yield of traditional technology, we then plot averages of the residuals for each country-crop cell. This figure indicates that there is no systematic relationship between the modern potential yield premium and the level of economic development of a country.

Figure A.3: Land Use against Potential Yield

(a) Land Use against “Traditional” Potential Yield (b) Land Use against “Modern” Potential Yield

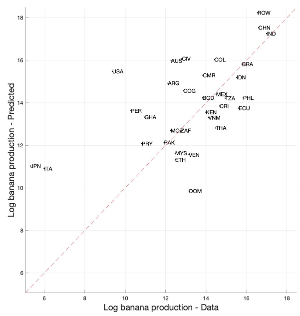


Notes: This figure plots aggregate land use of crops against potential yields of traditional in Panel (a), and of modern in Panel (b). The average country-level potential yield of a crop is the aggregate of potential yields of the corresponding crop in all fields within the country. Values of land use and potential yields of every crop are relative to those of corn in every country. Every point in the figure represents a crop-country pair and those of corn are dropped since their logs are zero by structure.

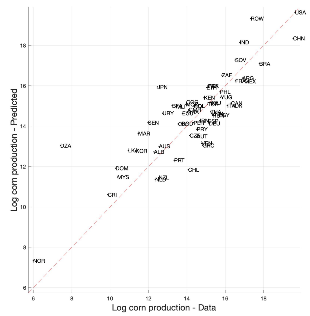
G.2.2 Model Fit

Figure A.4: Model Fit with respect to Production Quantity of Crops

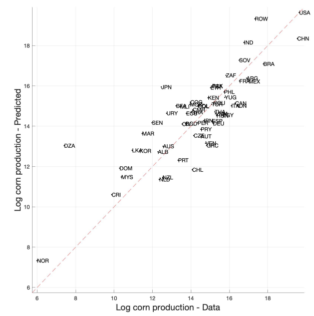
(a) Banana



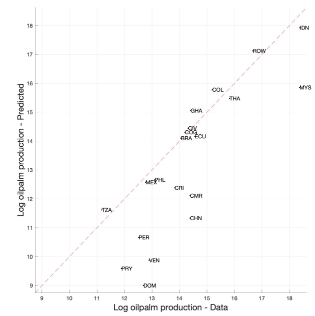
(b) Corn



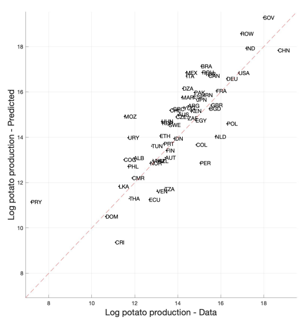
(c) Cotton



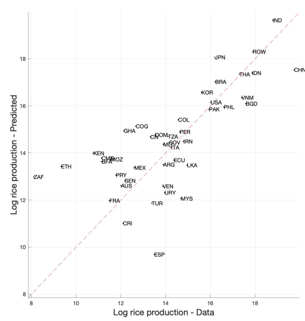
(d) Palm



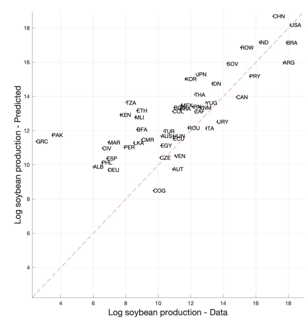
(e) Potato



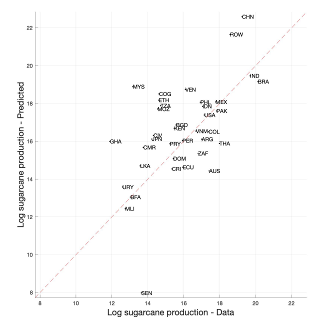
(f) Rice



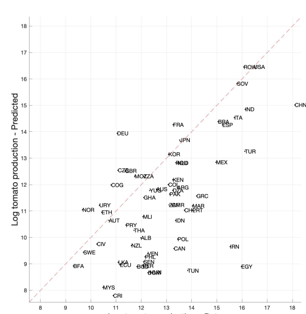
(g) Soybean



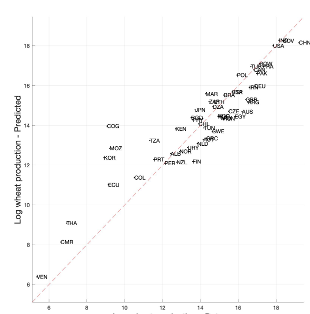
(h) Sugarcane



(i) Tomato

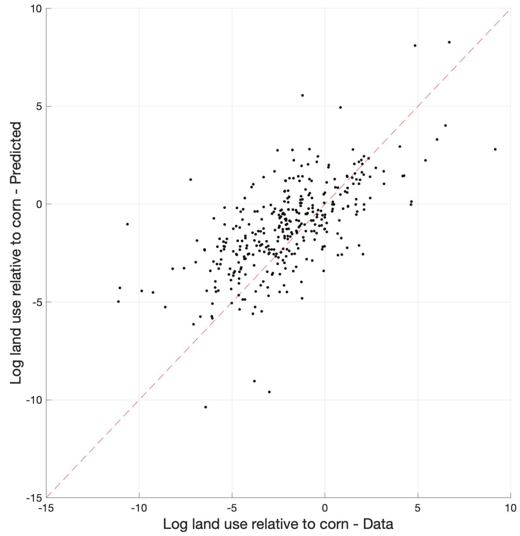


(j) Wheat



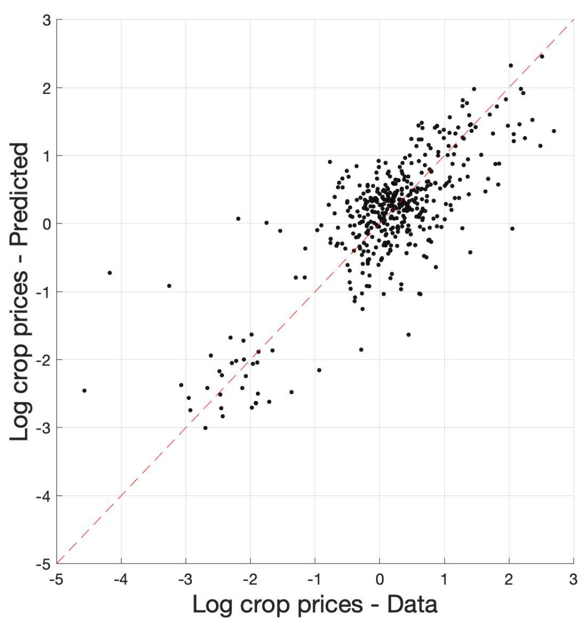
Notes: This Figure shows the fit of the model with respect to output quantities of each crop across countries.

Figure A.5: Model Fit with respect to Land Use of Crops



Notes: This figure plots land use of crops as predicted by the model against the data. Values of land use of every crop are relative to those of corn in every country. Every point in the figure represents a crop-country pair and those of corn are dropped since their logs are zero by structure.

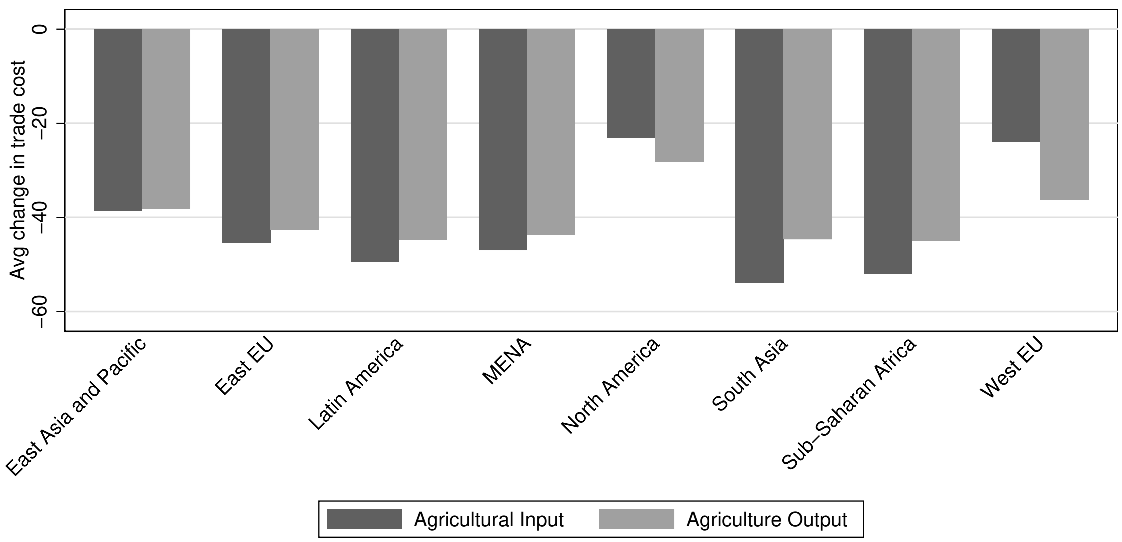
Figure A.6: Model Fit with respect to Prices of Crops



Notes: This figure plots producer prices of crops as predicted by the model against the data. Prices of every crop are reported as relative to the average global price of corn. Every point in the figure represents a crop-country pair and those of corn are dropped since their logs are zero by structure.

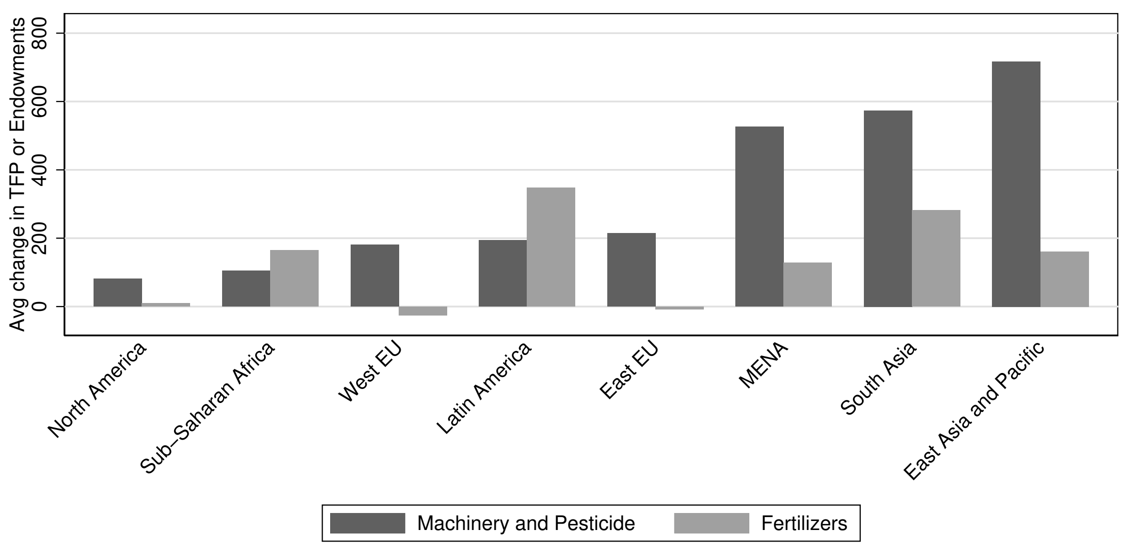
G.2.3 Counterfactual Exercises

Figure A.7: Changes in Trade Cost by Region between 1980 and 2007



Notes: This figure shows changes in trade costs of agricultural inputs and agricultural outputs between 1980 and 2007, weighted for every region based on trade flows of countries in that region. See Section E.1 for details on our estimation of trade costs.

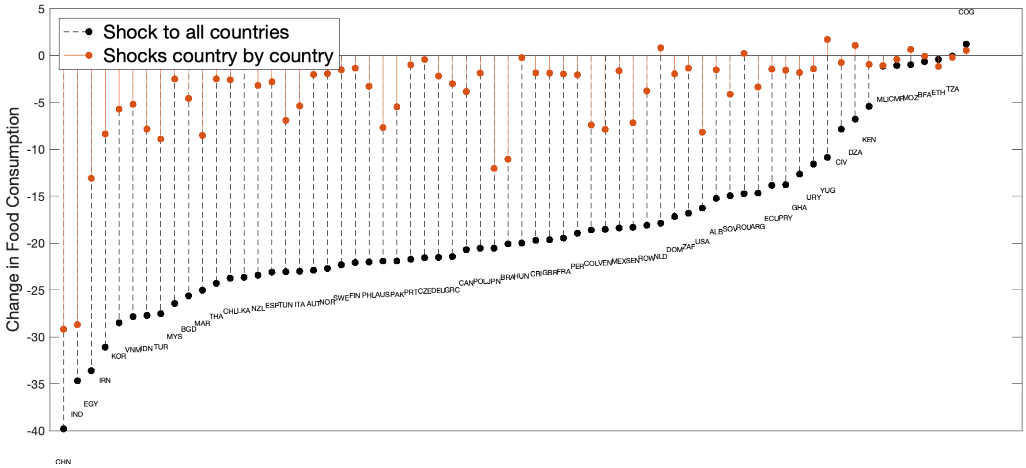
Figure A.8: Changes in Productivity in Non-agriculture by Region between 1980 and 2007



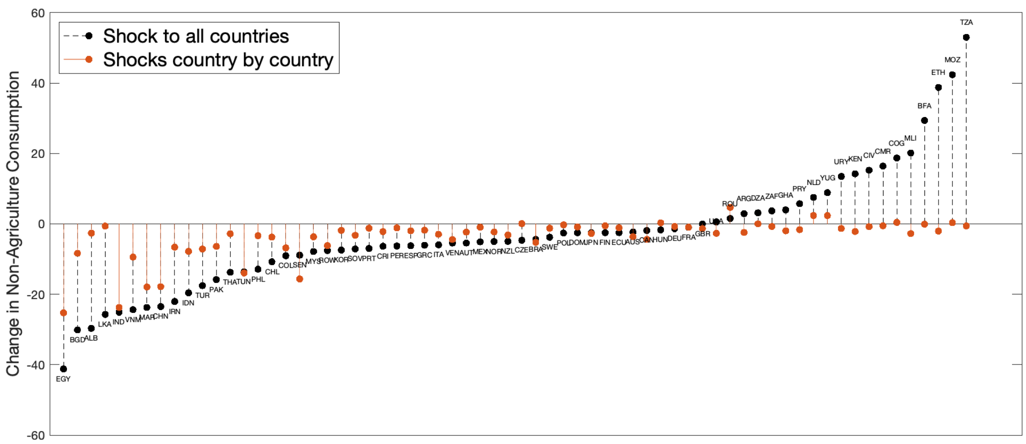
Notes: This table shows changes in productivity of agricultural inputs between 1980 and 2007, weighted for every region based on GDPof countries in that region. See Section E.2 for details on our calibration of productivity changes.

Figure A.9: The Impact of Changes in Productivity of Agricultural Inputs on Food Consumption

(a) Food Consumption

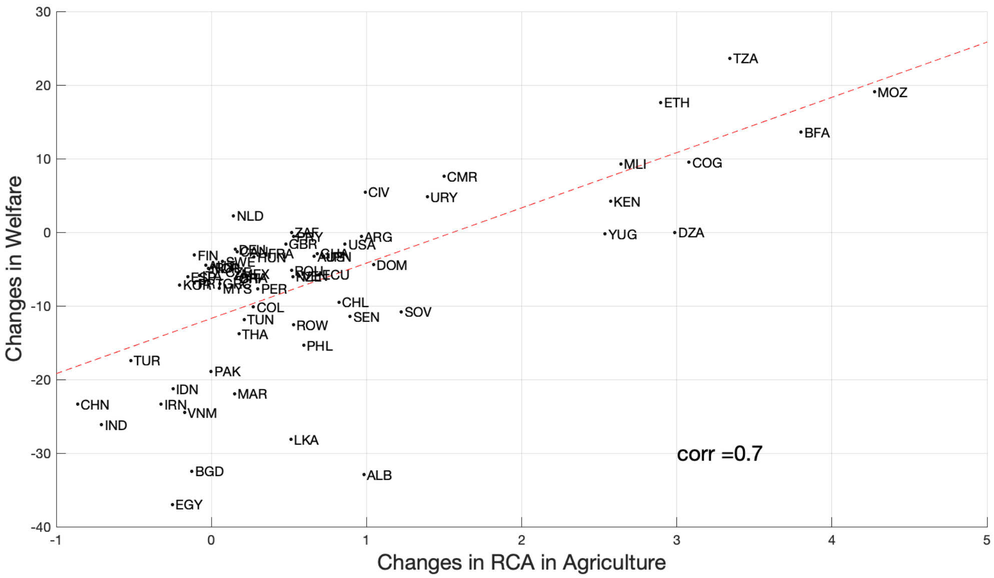


(b) Non-agricultural Consumption



Notes: These figures report results for (i) 66 counterfactuals in which we re-calibrate the productivity of agricultural inputs country by country, one at a time, and (ii) one counterfactual in which we re-calibrate the productivity of agricultural inputs in all countries at once. The red dots represent the outcome for the country whose productivity parameters are re-calibrated in the case of (i), and the black dots represent the outcome in the case of (ii). Panel (a) and Panel (b) report the percentage change to the consumption of food (agriculture goods) and nonagriculture goods.

Figure A.10: Percentage Changes in Welfare against Percentage Changes in Revealed Comparative Advantage for the Counterfactual with Changes to Productivities of Agricultural Inputs in All Countries



Notes: This figure plots percentage changes to welfare against percentage changes to the revealed comparative advantage (RCA) in agriculture in the counterfactual in which we set productivities of the agricultural input sector at their levels in 1980. The RCA is the Balassa index given by $RCA_i = (EXP_{i1}/EXP_{i0}) / (\sum EXP_{i1} / \sum EXP_{i0})$, where EXP_{i0} and EXP_{i1} are respectively exports of agriculture and nonagriculture in country i.