Global Trade and Margins of Productivity in Agriculture

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Abstract

We study the effects of globalization on agricultural productivity across the world. We develop a multi-country general equilibrium model that incorporates choices of crops and technologies in agricultural production at the micro-level of fields covering the surface of the earth. We estimate our model using field level data on potential yields of crops under different technologies. We evaluate the productivity gains across countries from reductions in trade costs of agricultural inputs between 1980 and 2010. We find large gains in agricultural productivity and welfare at the global level associated with a shift from traditional (labor-intensive) technologies to modern (input-intensive) ones. The effects are largely heterogeneous across countries, with efficiency losses in countries that fell behind in the process of globalization.

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1 Introduction

In the past few decades, agricultural productivity has grown remarkably around the world. This spectacular growth has been important to sustain the global demand for food, and to increase the economy-wide efficiency in many countries. During this period, there has been also a dramatic fall in international barriers to trade. This phenomenon, often referred to as globalization, was consequential for crop specialization around the world. In addition, it facilitated in many countries the imports of agricultural inputs that are required to adopt modern technologies. Taking into account technology adoption, input intensification, and crop specialization is therefore important for evaluating the effects of globalization on agricultural productivity around the world.

In this paper, we develop a general equilibrium framework to study how globalization shapes agricultural productivity around the world through crop specialization and technology choice. Using our framework, we address a few questions. What were the consequences of globalization for land and labor productivity of crops across the world geography? How important was the access to internationally supplied inputs for the adoption of modern, input-intensive technologies? Which countries did gained and which of them did lose from these global trends?

Our analysis bridges two isolated literatures examining the sources of agricultural productivity gains: one that highlights the adoption of labor-saving and input-intensive technologies; another that studies the role of crop specialization through international comparative advantage.[1] In our framework agricultural producers can (i) exploit productivity gains through crop specialization intrinsic in the micro-level heterogeneity of land, and (ii) procure internationally supplied inputs used in modern, input-intensive technologies. We bring our model to micro-level data on potential yields of crops under different technologies at the level of fields covering the world geography. We use these data to construct for each field a production possibility frontier that governs choices of crops and technologies.

We begin our investigation by documenting a few empirical patterns. Using country-level data, we show that measures of agricultural productivity and the import content of agricultural inputs have grown substantially over the past few decades. In addition, the cost shares of inputs such as fertilizers, pesticides, and farm machinery, are systematically larger in countries with higher agricultural productivity. Using field-level data, we show

[1]For the former, e.g. see Gollin, Parente, and Rogerson (2007), Restuccia, Yang, and Zhu (2008); and for the latter, e.g. see Tombe (2015), Costinot, Donaldson, and Smith (2016), Sotelo (2019).

that there are large premia in the potential yield of crops brought by modern, input-intensive technologies over the traditional, labor-intensive ones. These patterns suggest that productivity gains in agriculture are associated with production technologies that use agricultural inputs intensively, and that these inputs are by and large procured in most countries through imports.

Next, we develop a general equilibrium framework in which farmers choose which crops to grow and with which technology to grow them. A technology is characterized by factor and input intensities. Therefore, higher relative wages and lower relative input prices encourage the use of labor-saving, input-intensive technologies. To manage the margins of productivity adjustment, we use a nested choice structure based on a generalized Fréchet distribution. This parsimonious formulation allows for a different elasticity for each margin of adjustment, i.e. across crops and across technologies within crops. We demonstrate how these elasticities govern the curvature of the PPF which determines how agricultural producers respond to exogenous changes in trade costs and productivities.

We estimate our model in two steps. First, we estimate elasticities of substitution across crops and supplying countries as in Costinot, Donaldson, and Smith (2016). Second, using our estimates of the demand side parameters, we estimate the two production elasticities via generalized method of moments. We construct our moments based on field-level variations in yields and cross-country variations in input use. In doing so, we also make use of field-level data on actual yields from the United States. The field-level variations in actual yields identifies the elasticity that governs choices of crops, and cross-country variations in the cost share of agricultural inputs identifies the elasticity that governs choices of technology. In addition to in-sample variables, our model fits well out-of-sample data on employment and value added in agriculture.

We use our estimated model to run counterfactual exercises where we evaluate the effects of globalization on agricultural productivity and welfare around the world. In particular, we consider a counterfactual in which costs of trade in agricultural inputs are set to their estimated level in 1980, and compare the resulting equilibrium with that in the baseline of 2010. We find that the reallocation of agricultural inputs across locations of agricultural production would induce a notable increase in the share of land allocated to modern technologies. The shift toward modern technologies would help agriculture producers increase land and labor productivities of crops in which they have a comparative advantage, resulting in higher real consumption of agriculture. Despite efficiency gains at the global scale, due to general equilibrium effects these gains are heterogeneous across countries. Countries that fell behind in the process of globalization would end up facing relatively higher prices of agricultural inputs. Consequently, in these countries incentives would be lower for adopting modern technologies, creating a barrier for their economic development. Yet, at the global level, due to lower trade costs of agricultural inputs, yields would rise by 2% to 15% across crops, real consumption of agriculture would increase by 2.41%, and overall welfare would rise by by 0.74%.

Related Literature

Our paper bridges several literatures. First, our modeling approach contributes to efforts to integrate field-level datasets on climate and agriculture into general equilibrium frameworks. Second, we complement studies on the role of agriculture productivity in economic development.

Our approach builds on two recent papers that model the land heterogeneity driving crop choices using tools from Eaton and Kortum (2002). First, Sotelo (2019) who uses regional-level data from Peru to study the effects of internal trade costs on agricultural productivity. Second, Costinot, Donaldson, and Smith (2016) who combine country and field level data to evaluate the effects of changes in agricultural suitability induced by climate change.[2] Both of these papers use agricultural suitability data from FAO-GAEZ based on a single agricultural technology in their empirical analysis. Here, we make use of data on agricultural suitability on two technologies, modern and traditional, to study the effects of globalization on the modernization of agricultural production. To do so, we bring a nested choice structure that gives rise to different elasticities governing choices of crops and technologies.[3]

This paper contributes to growing research on agricultural trade and economic development (Tombe, 2015; Gafaro and Pellegrina, 2019; Porteous, 2016; Costinot and Donaldson, 2014; Fajgelbaum and Redding, 2019; Allen and Atkin, 2016; Donaldson, 2018; Pellegrina, 2019). These studies have developed general equilibrium frameworks to examine the effects of trade, domestic or international, on agricultural productivity. Closer to our modeling ap-

[2]Gouel and Laborde (2018) extend Costinot, Donaldson, and Smith (2016) to a wider set of agricultural activities — more crops as well as livestock— incorporating a flexible demand structure with elasticities estimated in the literature on agricultural economics.

[3] Our formulation bears similarities to a number of studies that use generalized extreme value distributions of productivities in trade models (Arkolakis, Ramondo, Rodríguez-Clare, and Yeaple, 2018; Lind and Ramondo, 2018; Lashkaripour and Lugovskyy, 2018).

proach, in a recent paper, Bergquist, Faber, Fally, Hoelzlein, Miguel, and Rodriguez-Clare (2019) analyze the general equilibrium effects of scaling up policy interventions using farm-level data from Uganda.[4] By emphasizing the role of agricultural inputs in agricultural trade, we contribute to efforts to incorporate input-output structures into quantitative trade models such as Caliendo and Parro (2015).[5] Different from this literature, which assumes exogenous cost shares of inputs based on input-output tables, here we allow differences in cost shares to reflect endogenous technology choices.

This paper also relates to a large body of research in agricultural economics that examine farmers' response to government policies in their choices of land use or crop supply, e.g. see Lee and Helmberger (1985) for a pioneer study, Taheripour and Tyner (2013) for general equilibrium land use changes in response to biofuel programs and Hertel (2002) and Hertel (2013) for a review of the literature on the application of computation general equilibrium models in agriculture. Moreover, we complement studies that examine the role of trade in commodities as crucial inputs to downstream sectors such as Farrokhi (2019) and Fally and Sayre (2018).

Lastly, our paper relates to research in macroeconomics examining the role of agriculture productivity in the process of economic development, e.g. Caselli (2005). Among recent studies, Lagakos and Waugh (2013) and Gollin, Lagakos, and Waugh (2014) explore sources of cross-country labor productivity differences in agriculture, and Donovan (2017) studies the role of insurance markets in agriculture input use across countries. Closest to our paper is Gollin, Parente, and Rogerson (2007), who emphasize labor-saving, input-intensive technologies as a key mechanism driving the gains in agriculture productivity and structural change. Our contribution to these studies are two-fold. First, we put the analysis of agricultural productivity into a global perspective. Second, we connect the macro-level analysis to micro-level heterogeneity intrinsic in conditions of land and climate across the world geography.

The rest of this paper is organized as follows. In Section 2, we present the data and empirical patterns that motivate our model, which we develop in Section 3. We estimate our model in Section 4, and run quantitative exercises in Section 5.

[4] Their framework is similar to ours in that they model land heterogeneity allowing for modern and traditional technologies. Different from our approach, since they use the method of hat algebra, they do not require data on land suitabilities for their analysis. Their approach, however, requires detailed farm-level which is not available at a global scale.

[5] See Costinot and Rodríguez-Clare (2014) for a survey on tools and applications in this literature.

2 Data & Empirical Patterns

This section describes the data used in our analysis and presents empirical patterns about agricultural production and trade that inform the formulation of our model.

2.1 Data

We describe our data in two parts: at the aggregate level of countries, and at the disaggregated level of fields. Here, we highlight main features of our data, and leave a thorough description to the appendix.

2.1.1 Country-level data

We have collected information from several sources to construct a panel of country-level data on gross output, bilateral trade, and expenditure of crops, agricultural input categories, and nonagricultural goods (see Table A.1). As for agricultural inputs, we focus on fertilizers, pesticides, and agricultural machinery, which are exclusively used as inputs into agriculture production.[6] We complement this panel data with information on employment, cropland, share of expenditure on agriculture, value added in agriculture and non-agriculture sectors as well as standard macroeconomic indicators such as GDP and population.

Our final dataset contains the 69 countries with the largest agricultural value added in the world (excluding countries with missing data) plus one region that aggregates remaining countries which we refer to as the rest of the world (ROW). We include 10 major crops in our analysis: banana, cotton, corn, palm oil, potato, rice, soybean, sugarcane, tomato, and wheat.

Table 1 reports summary of statistics for our country-level data. For each variable, the table reports aggregate values in year 2010 for eight regions that cover the world geography and the growth at the global level between 1980 and 2010. We normalize GDP per capita and agricultural value-added per worker such that the GDP per capita in North America is set at unity. As it has been previously documented (e.g Gollin, Lagakos, and Waugh (2014)), in our data the valued added per worker in agriculture is typically lower than its economy-wide counterpart, and the gap between the two decreases with countries' income per capita.

[6] Data on these three input categories are available with sufficient coverage and quality. Furthermore, they are frequently cited as the most crucial inputs. For example, FAO-STAT provides data only for these three agricultural inputs. Another important input category is seeds, but we do not have data to include them in our empirical analysis.

Table 1: Summary Statistics

	Values for 2007								Global Growth Rate 1980-2007
	North America	East Asia & Pacific	East Europe	Latin America	MENA	South Asia	SSA	West Europe	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP per capita	1.00	0.14	0.15	0.14	0.12	0.03	0.02	0.77	202.5
VA per worker in ag	0.67	0.06	0.03	0.04	0.03	0.01	0.01	0.29	124.8
Cost share of inputs	0.19	0.10	0.13	0.11	0.10	0.08	0.06	0.17	30.6
Import share of inputs	0.35	0.18	0.63	0.57	0.33	0.31	0.77	0.64	73.0
- Machinery	0.34	0.14	0.70	0.43	0.33	0.12	0.82	0.57	70.9
- Fertilizer	0.50	0.19	0.46	0.72	0.30	0.41	0.87	0.81	56.4
- Pesticide	0.25	0.22	0.50	0.53	0.42	0.36	0.58	0.71	122.9
Number of countries	2	5	7	12	7	7	13	16	

Notes: Value added data are normalized such that economy-wide value added per worker in North America is set at unity. SSA stands for Sub-Saharan Africa. MENA stands for Middle East and North Africa region. For every region the reported number is the aggregate value for all countries in that region. Import share of inputs is total imports divided by total expenditure.

Some key observations emerge from examining the cost share of inputs and import share of agricultural input expenditure. Specifically, "cost share of inputs" is the ratio of expenditures on agricultural inputs relative to gross output in agriculture, and "import share of inputs" is the ratio of imports to total expenditure of agricultural inputs. Cost share of inputs is the highest in North America reaching 40%, and the lowest in Sub-Saharan Africa only reaching 8%. In addition, cost share of inputs has grown by 110% between 1980 and 2010 for the median country, highlighting a global trend toward input intensification in agricultural production.

Turning to the import share of inputs, there are large variations across countries, and across input categories within a country. Most countries depend on international trade to procure at least one of fertilizers, pesticides, and farm machinery. This observation in turn reflects the high geographic concentration in the production of agricultural inputs across countries. The production of fertilizers is concentrated in a subset of countries that have the required natural resources. The production of pesticides and farm machinery requires chemical- and machinery-related technologies that might be unavailable to low-income countries. 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 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 the aggregate of inputs, the regional minimum share of imports is 13%, whereas the maximum exceeds 63%. For most European and Latin American countries imports account for about a half of their expenditure on agricultural inputs. These figures suggest that intermediate inputs account for a notable share of agricultural production costs, and that imports play an important role in the use of agricultural inputs. We report in the appendix additional figures at the level of individual countries.

2.1.2 Field-level data

The field-level data is given at the level of agro-ecological zones (AEZs). An AEZ is a 5 minute by 5 minute latitude/longitude grid, which encompasses an area of approximately 10 km by 10 km. We integrate two field-level datasets, one on potential yields of crops that represent the spatial agro-ecological suitability of crops by the type of technology, the other on actual yields based on national censuses for a subset of countries.

Our first set of field-level data provides information on the potential yields of crops, taken from Global Agro-Ecological Zones project organized by the Food and Agriculture Organization (FAO) and the International Institute for Applied Systems Analysis (henceforth, FAO-GAEZ). The "potential yield" of a crop in a field is defined as the maximum attainable yield of that crop (measured in tons per hectare) if the entire field were allocated to that crop. Potential yields are estimated based on agronomic models that use information on local conditions of land such as soil types, elevation, and land gradient and of climate such as rainfall, humidity, and temperature. As such, these measures capture local agro-ecological characteristics of a field, but not local market conditions related to crop and input prices. This distinction will be important later when we calibrate our model. We use data on potential yields for low and high input technologies. The low-input technology corresponds to a traditional farming activity where production is labor intensive and there is minimum to no use of agricultural inputs. The high-input technology corresponds to a modern system where production is input-intensive. Hereafter, we thus call low and high input technologies, respectively, "traditional" and "modern".[7] In addition, we define "modern potential yield premium" as the ratio of potential yield of modern to that of traditional technology. Our final data contain 1,300,427 fields from FAO-GAEZ with nonzero records of traditional

[7] According to the definition from FAO-GAEZ, the low-input technology represents a production regime with "no application of nutrients, no use of chemicals for pest and disease control" and the high-input technology a production that is "fully mechanized with low labor intensity and uses optimum applications of nutrients and chemical pest, disease and weed control."

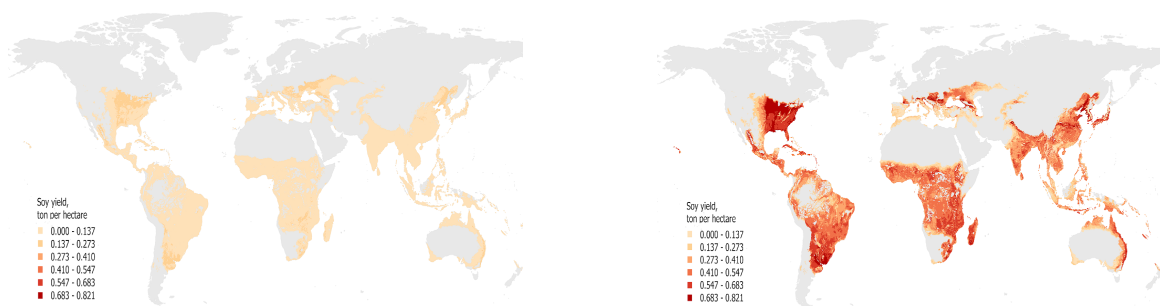
and modern potential yields of at least one crop. As an example of the data, Figure 1 plots potential yields of soybean based on traditional (low-input) and modern (high-input) technologies across the world geography.

Our second set of field-level data comes from EarthStat.[8] These data contain field-level information on actual yields of crops circa year 2000 and are constructed based on national, state, and county level census statistics. A key limitation here is that the data does not always capture the field-level heterogeneity that is required for our analysis. In regions where data from agricultural censuses are not available at fine levels of disaggregation, aggregate data from national level are downscaled to the AEZ level. In contrast, for countries where detailed census information are available, the mapping is between disaggregated units, such as counties in the USA. For these reasons, we take the EarthStat field-level data of only the United States, which is constructed based on disaggregated information at the county level with a sufficiently large coverage of crops.[9]

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

a. Traditional

b. Modern



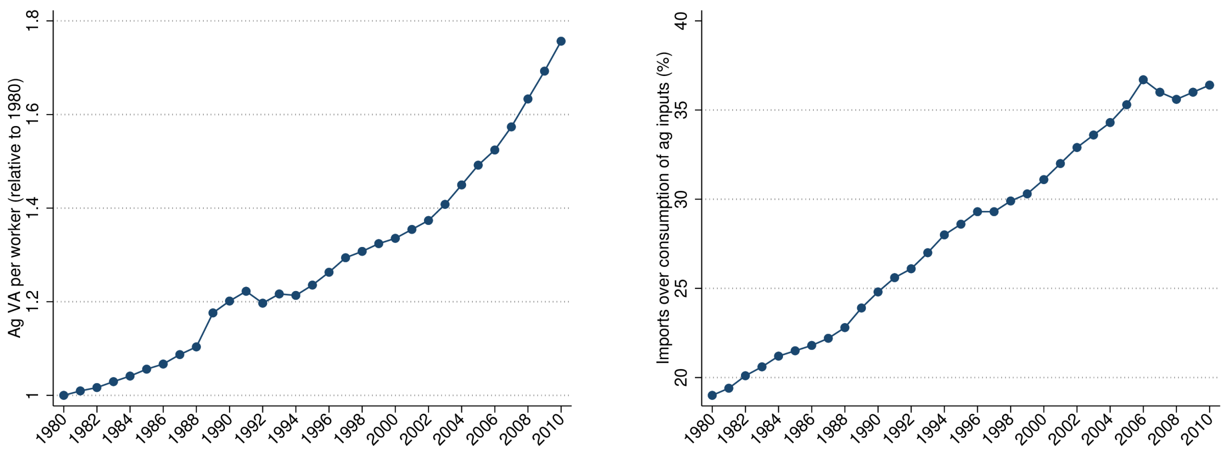
Notes: FAO-GAEZ potential yields are the maximum attainable yields of soybean in every field if the entire area of the field is allocated to soybean, using traditional (low-input) technology, and modern (high-input) technology.

[8]EarthStat is a collaboration between the Global Landscape 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 to construct field-level dataset on agriculture at the global level.

[9]To the best of our knowledge, we are among the first in economics to merge census-based actual yields from EarthStat with science-based potential yields from FAO-GAEZ at the global scale for a general equilibrium analysis. There is a growing body of research in agriculture and climate sciences using EarthStat data at a global scale. For examples, see Deryng, Conway, Ramankutty, Price, and Warren (2014), Niedertscheider, Kastner, Fetzel, Haberl, Kroisleitner, Plutzar, and Erb (2016), Foley, Ramankutty, Brauman, Cassidy, Gerber, Johnston, Mueller, OConnell, Ray, West, et al. (2011) and Mueller, Gerber, Johnston, Ray, Ramankutty, and Foley (2012). For a detailed description of the construction of the dataset, see Monfreda, Ramankutty, and Foley (2008).

Figure 2: Value Added per Worker & Share of Imports in Agricultural Input Use at the Global Level (1980-2010).

a. Value added per worker in agriculture   b. Share of imports in agricultural input use



Notes: This figure shows that the large increase in agricultural output per worker and agricultural land between 1980 and 2010 coincided with the increase in the share of imports of agricultural inputs between 1980 and 2010.

2.2 Empirical Patterns

We present four empirical patterns that motivate the formulation of our model. The first two empirical patterns highlight the importance of agricultural input use and their imports over time and across countries. The last two empirical patterns present variations in the field level data which we incorporate into our model.

Empirical Pattern 1. At the global level, agricultural value added per worker and the share of imports in agricultural input use have increased substantially between 1980 and 2010.

Agricultural value added per worker has increased at the global level by approximately 80% between 1980 and 2010 (Figure 2). This substantial growth in agricultural productivity was accompanied by a striking growth of the share of imports in agricultural input use. Figure 2 panel (b) illustrates the evolution of import share in the use of agricultural inputs at the global scale. This share grew from 12% in 1980 to 33% in 2010. Moreover, the extent to which imports account for agricultural input use varies largely across countries and across the three categories of inputs. We illustrate these cross-country and cross-input variations in the appendix. This heterogeneity illustrates that many countries largely depend on imports to procure all or at least one of the agricultural input categories.

Empirical Pattern 2. Across countries, measures of agricultural input intensity are strongly correlated with GDP per capita.

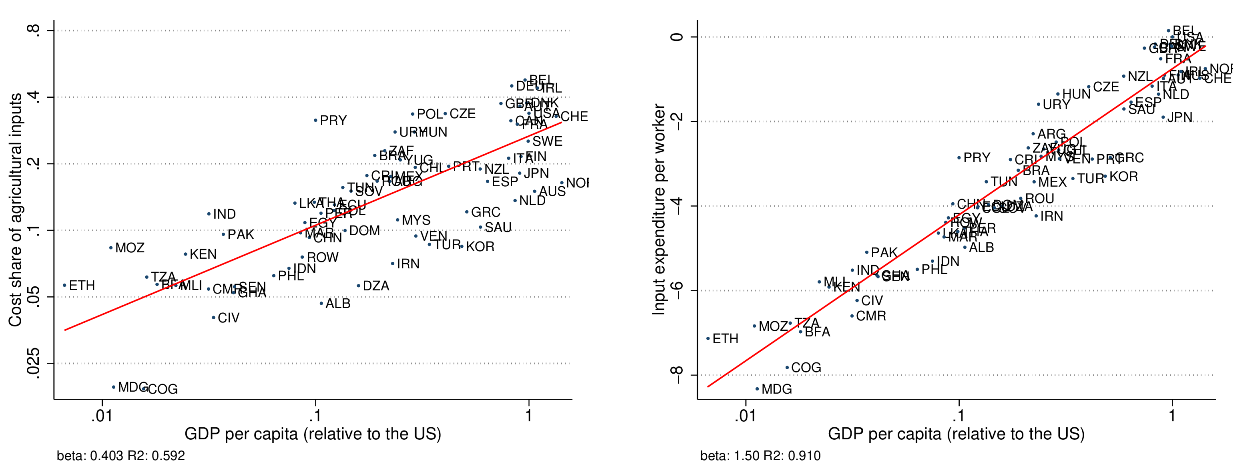
In the previous empirical pattern, we highlighted the increasing role of trade in the use of agricultural inputs. We now show that agricultural input intensity across countries is strongly associated with the level of development. In Figure 3 panel a, we show the scatter plot of agricultural cost share of inputs against GDP per capita across countries. As a statistical correlation across countries, 1% increase in log GDP per capita is associated with 0.34% increase in log cost share of inputs.

This relationship in turn manifests itself as a correlation between measures of agriculture productivity and input intensity. Figure 3b shows that agriculture input use per worker is strongly correlated with GDP per capita. The cross-country variations in measures of development and input intensity in agriculture are enormous. For example, agricultural value added per worker in the United States is 40 times larger than that in Ivory Coast, with the cost share of inputs being around 41% and 6% in the respective countries.

The combination of Empirical Patterns 1 and 2 indicates that the increasing access to internationally supplied inputs was a crucial channel though which globalization affected agricultural productivities. With this takeaway in mind, we now turn to empirical patterns that emerge from our field-level data.

Figure 3: Agricultural Input Intensity versus GDP per capita.

a. Cost share of inputs | b. Input expenditure per worker

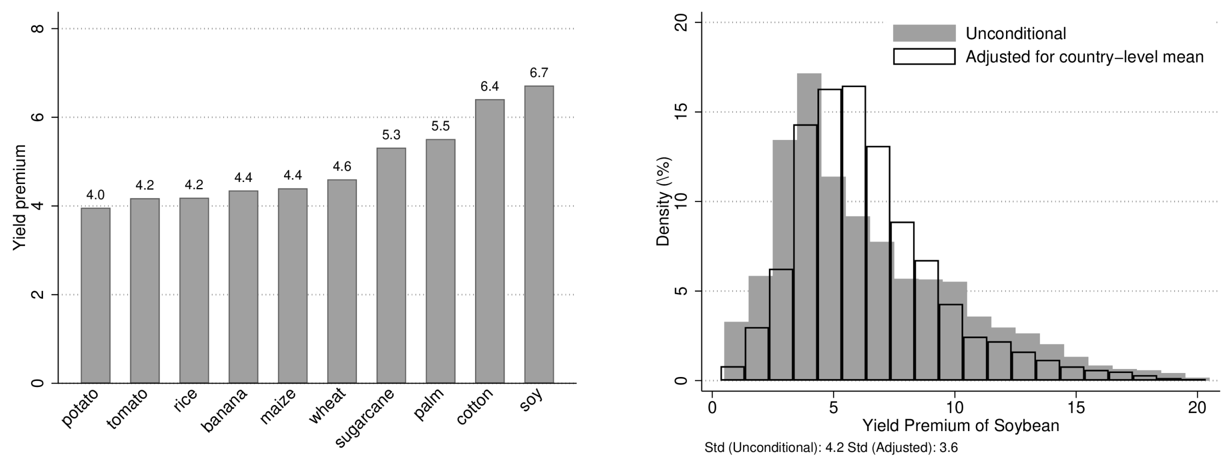


Notes: This figure plots for countries in year 2010 their GDP per capita against agricultural input expenditure per worker in panel (a) and cost share of inputs in panel (b).

Figure 4: Potential yield premium

a. Average across crops

b. Distribution across fields for soybean



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.

Empirical Pattern 3. The potential yield of the high-input (modern) technology over the low-input (traditional) technology is typically large and varies substantially across fields and crops.

Using FAO-GAEZ data on potential yields of modern and traditional technologies, we document that substantial productivity gains can be made by shifting the production towards input-intensive technologies. Figure 4 panel (a) shows the average yield premium of modern (high-input) technology over traditional (low-input) technology across fields in the world. Modern potential yield premia are, on average, in the range of four to seven across crops. For example, an average field around the world would yield 4.6 times more wheat using modern than traditional technology if the entire field was allocated to wheat. This average global premium is at minimum 4 in the case of potato, and at maximum 6.7 for soybean.

Focusing on the case of soybeans, Figure 4 panel (b) shows that modern potential yield premia vary substantially across the world geography. The global average premium for soybean hides the vast heterogeneity across fields and the relatively fat right tail of the distribution. Specifically, the 5th, 50th, and 95th percentile are 1.9, 5.5, and 14.9. Figure 4 panel (b) also shows that, even if we adjust the premium by the average in every country to control for between-country variations[10], remarkable heterogeneity remains in the premia across fields.

[10]Our adjustment is given by: (field-level - country-level mean) + global mean.

Pattern 4. Across fields, actual yields are (a) negatively correlated with land shares, and (b) positively correlated with potential yield premia of modern technology.

We now examine how the premia for modern technology translate into variations in actual yields. We notice first that examining the relationship between actual and potential yields is somewhat challenging because actual yields reflect *choices* in addition to potentials. If the entire area of a field was allocated to a crop, then by definition actual yield would equal potential yield. However, only a fraction of every field is allocated to agriculture production, in which typically multiple crops grow. When farmers reduce the share of land allocated to a given crop, they tend to keep areas within a field that are more suitable for the production of that crop. Hence, the smaller the fraction of a field dedicated to a crop, the greater the actual yield compared to the potential yield. For this reason, the land share of a crop contains information about the endogenous choices of crops.

This intuition is at the core of the model by Costinot, Donaldson, and Smith (2016). Accordingly, we make our empirical analysis operational in a simple way at this stage, by borrowing an equation that is implied by Costinot, Donaldson, and Smith (2016). Specifically, this equation requires that log of actual yield relative to potential yield of a crop in a field have a negative relationship with log land share of that crop in that field. We run a regression based on this specification using data on actual yields from the United States. Column (1) of Table 2 shows that this relationship between land share and yield is indeed the case in the data. We emphasize, however, that we are not identifying any particular parameter here. Our goal is rather to take a first look into our field-level data to learn about basic correlations in line with the priors set by the literature as well as our intuition. Column (2) shows that, controlling for crop land share and traditional potential yield, actual yields are systematically larger in fields where the potential yield premia are greater.[11]

Taken together, Empirical Patterns 3 and 4 indicate that there are large variations in potential productivity of land across fields even within countries, and that technological

[11] Specifically, for crop k and field f let $y_{k,f}$ be actual yield, $\bar{y}_{k,f}$ be potential yield, and $\pi_{k,f}$ be land share. Here, there is no notion of technology and the potential yield might be based on either traditional or modern, but not both. Then, the relationship is $y_{k,f} = \bar{y}_{k,f}(\pi_{k,f})^{\beta}$ or $\log(y_{k,f}/\bar{y}_{k,f}) = \beta \log(\pi_{k,f})$. Here, $\beta = -1/\theta$, where $\theta > 1$ is the dispersion parameter of Fréchet distribution that disciplines the heterogeneity of potential yields across fields. A higher $|\beta|$ or a lower θ means that potential yields are more heterogeneous across fields. As a result, the opportunity cost of an expansion in land use, which is reflected by $\beta < 0$, would be greater if $|\beta|$ was smaller. In column (1), $\bar{y}_{k,f}$ is the potential yield of traditional technology, and regression results remain similar if we replace it with that of modern. In column (2), we replace $\bar{y}_{k,f}$ with a geometric mean of traditional potential yield $\bar{y}^{L}_{k,f}$ and modern potential yield $\bar{y}^{H}_{k,f}$, i.e. $\bar{y}_{k,f} = (\bar{y}^{L}_{k,f})^{1-\alpha}(\bar{y}^{H}_{k,f})^{\alpha}$. Then, the resulting regression equation is $\log(y^{f}_{k}/\bar{y}^{L}_{k,f}) = \alpha \log(y^{H}_{k,f}/\bar{y}^{L}_{k,f}) + \beta \log(\pi^{f}_{k})$. These OLS regressions overestimate β and hence θ because the unobserved land productivity is positively correlated with land share. Consistent with our prior, here the implied θ, that is around 8, is larger than 2.7 estimated by Costinot, Donaldson, and Smith (2016).

shifts at the field level from traditional to modern technologies can have substantial effects on yields.

Table 2: Relationships between Yields, Land Share and Yield Premium

	Log Actual/Trad Yield	Log Actual/Trad Yield
	(1)	(2)
Log Land Share	-0.124***	-0.126***
	(0.001)	(0.001)
Log Modern/Trad Yield		0.049***
		(0.008)
R2	0.121	0.122
Obs	203183	203183

Notes: Robust standard errors clustered at the field level in parenthesis. *** denotes significance at 1% level, ** significance at 5% and * at 10%. Every observation is for a crop-field pair, and the sample contains fields in the United States.

From the empirical patterns to the theory

In summary, our empirical patterns show that the global growth in agricultural productivity in the past few decades has coincided with a remarkable rise of globalization in agricultural inputs, that there are large yield premia for the use of high-input agricultural technologies across the world geography, and that larger premia are associated with larger observed yields. These observations motivate the formulation of a model in which adoption of input-intensive technologies can increase agricultural productivities and access to internationally supplied inputs encourage the adoption of these input-intensive technologies. Finally, our modeling choices are also motivated by two additional empirical patterns that are well-documented elsewhere: the nonhomotheticty in food consumption and the importance of land heterogeneity to study crop specialization.

3 Model

3.1 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 an outside 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 technique characterized by input and factor intensities. Specifically, technique 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,

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

A set $\mathcal{F}_n$ of fields f, each with area L_n^f, characterizes the total land in country n, where $\sum_{f \in \mathcal{F}_n} L_n^f = L_n$. Our setup allows for differences in agroclimatic conditions at the level of fields, meaning that yields associated with producing a crop-technique pair (k, τ) are heterogeneous across fields $f \in \mathcal{F}_n$. Labor is homogeneous and freely mobile across productive activities within countries. Endowments of fertilizers are used in the production of processed fertilizers as an agricultural input. All goods $g \in \mathcal{G}$ are tradeable, and markets are perfectly competitive.

3.2 Consumption and Trade

Every good $g \in \mathcal{G}$ is differentiated by the origin of production. We denote by $C_{ni,g}$ the consumption of good g in country n originated from country i, and by $C_{n,g}$ the aggregate consumption of good g as a CES combination of varieties across origin countries,

$$C_{n,g} = \left[\sum_{i \in \mathcal{N}} (b_{ni,g})^{1/\sigma_g} \left(C_{ni,g} \right)^{(\sigma_g - 1)/\sigma_g} \right]^{\sigma_g/(\sigma_g - 1)} \tag{1}$$

Here, $b_{ni,g}$ is a demand shifter, and $\sigma_g > 0$ is the elasticity of substitution of good g across countries (e.g. US corn vs Mexican corn). Sector-level bundles of consumption, C_n^s, with $s = 0$ for nonagriculture and $s = 1$ for agriculture, are

$$C_n^s = \begin{cases} C_{n,0} & \text{if } s = 0 \\ \left[\sum_{k \in \mathcal{K}} (b_{n,k})^{1/\kappa} (C_{n,k})^{(\kappa-1)/\kappa} \right]^{\kappa/(\kappa-1)} & \text{if } s = 1 \end{cases} \tag{2}$$

Here, $C_{n,0}$ and $C_{n,k}$ are given by equation (1), $b_{n,k}$ is a demand shifter, and $\kappa > 0$ is the elasticity of substitution across crops (e.g. corn vs wheat). The representative consumer in country n receives utility from the aggregate consumption, C_n, defined implicitly by the following non-homothetic CES representation,[12]

$$\sum_{s\in\{0,1\}} \left(b_n^s\right)^{\frac{1}{\eta}} \left(C_n\right)^{\frac{\varepsilon^s-\eta}{\eta}} \left(C_n^s\right)^{\frac{\eta-1}{\eta}} = 1, \tag{3}$$

where b_n^s is a demand shifter for sector $s \in \{0,1\}$; $\eta > 0$ is the elasticity of substitution across the consumption of nonagriculture C_n^0 and agriculture C_n^1 given by equation (2). $\varepsilon^s > 0$ is the elasticity of income with respect to sector s. If $\eta < 1$, agriculture and nonagriculture are complements; otherwise, they are substitutes. Sector s is a luxury if $\varepsilon^s > 1$, and a necessity if $\varepsilon^s < 1$. When $\varepsilon^s = 1$ for all s, the system collapses to CES preferences.

International trade in every good $g \in \mathcal{G}$ is subject to iceberg trade costs. To deliver 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 destined at n is $p_{ni,g} = p_{i,g}d_{ni,g}$, where $p_{i,g}$ denotes the producer price.

3.3 Production

Every field $f \in \mathcal{F}_i$ consists of a continuum of plots $\omega \in f$. The agriculture production in field f involves allocating crops $k \in \mathcal{K}$, using techniques $\tau \in \mathcal{T}$, to plots $\omega \in f$. The production technology is given by

$$Q_{i,k\tau}^f(\omega) = \bar{q}_{k\tau}\left(z_{i,k\tau}^f(\omega)L_{i,k\tau}^f(\omega)\right)^{\gamma_{k\tau}^L}\left(N_{i,k\tau}^f(\omega)\right)^{\gamma_{k\tau}^N}\left(M_{i,k\tau}^f(\omega)\right)^{\gamma_{k\tau}^M} \tag{4}$$

Here, $\bar{q}_{k\tau}$ is a constant scalar.[13] $z_{i,k\tau}^f(\omega)$ is the land productivity of plot ω for producing crop k using technique τ. $L_{i,k\tau}^f(\omega)$, $N_{i,k\tau}^f(\omega)$, and $M_{i,k\tau}^f(\omega)$ are respectively the use of land, labor, and material inputs. In addition, 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 $\gamma_{k\tau}^L = 1 - \gamma_{k\tau}^N - \gamma_{k\tau}^M \in [0,1]$ are, respectively, intensity parameters of labor, inputs, and land in production of crop k using technique τ. These intensity parameters characterize techniques which are either traditional $\tau = 0$ or modern $\tau = 1$.[14] The traditional technique,

[12] This system of preferences has several appealing features, discussed in details in Comin, Lashkari, and Mestieri (2015).

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

[14] Our modeling allows for any arbitrary number of techniques. The choice of two is made only for bringing the model to available data as explained in Section 2.

characterized by $\gamma_{k0}^{M} = 0$, is intensive in the use of labor with no requirement of using material inputs. The modern technique, characterized by $\gamma_{k1}^{M} > 0$, is intensive in the use of material inputs. The aggregate input use $M_{i,k\tau}^{f}(\omega)$ is a Cobb-Douglas combination of agricultural inputs,

$$M_{i,k\tau}^{f}(\omega) = \prod_{j \in \mathcal{J}} \left(M_{i,k\tau}^{j,f}(\omega) \right)^{\lambda_k^j} \tag{5}$$

where $M_{i,k\tau}^{j,f}(\omega)$ is the use of input j with $\lambda_k^j \in [0,1]$ as the share parameter, and $\sum_{j \in \mathcal{J}} \lambda_k^j = 1$. Share parameters are crop-specific reflecting the heterogeneity in their input intensities. No requirement of input use in the traditional technique ($\tau = 0$) implies $M_{i,k0}^{f}(\omega) = 0$.

We now derive returns to (or, rental price of) every plot of land ω, which we denote by $r_{i,k\tau}^{f}(\omega)$. Let the producer price of good $g \in \mathcal{G} \equiv \mathcal{O} \cup \mathcal{J} \cup \mathcal{K}$ in origin i be denoted by $p_{i,g}$, the consumer price index of g in destination i by $P_{i,g}$, and wage in country i by w_i. Furthermore, the price index of the bundle of agricultural inputs in destination i is given by $m_{i,k} = \prod_{j \in \mathcal{J}} (P_{i,j})^{\lambda_k^j}$. We derive in the appendix that by cost minimization, the unit cost of crop k using technique τ, $c_{i,k\tau}^{f}(\omega)$, equals

$$c_{i,k\tau}^{f}(\omega) = \Big(\frac{r_{i,k\tau}^{f}(\omega)}{z_{i,k\tau}^{f}(\omega)} \Big)^{\gamma_{k\tau}^{L}} \Big(w_i \Big)^{\gamma_{k\tau}^{N}} \Big(m_{i,k} \Big)^{\gamma_{k\tau}^{M}}$$

Since markets are perfectly competitive, profits in every field are pushed down to zero. Combining profit maximization and zero profit condition requires $c_{i,k\tau}^{f}(\omega) = p_{i,k}$. This delivers gross returns to plot ω, $r_{i,k\tau}^{f}(\omega)$, if assigned to crop-technique (k, τ),

$$r_{i,k\tau}^{f}(\omega) = z_{i,k\tau}^{f}(\omega) h_{i,k\tau} \tag{6}$$

$$\text{where} \quad h_{i,k\tau} = p_{i,k} \underbrace{\Big(\frac{w_i}{p_{i,k}} \Big)^{-\gamma_{k\tau}^{N}/\gamma_{k\tau}^{L}} \Big(\frac{m_{i,k}}{p_{i,k}} \Big)^{-\gamma_{k\tau}^{M}/\gamma_{k\tau}^{L}}}_{\widetilde{h}_{i,k\tau}} \tag{7}$$

Returns to crop-technique (k, τ) depends on land productivity $z_{i,k\tau}^{f}(\omega)$, and a component which we call $h_{i,k\tau}$ that summarizes the effect from market prices. The price-inclusive component, $h_{i,k\tau}$, rises in the output price $p_{i,k}$, and falls in the effective relative input price $\widetilde{h}_{i,k\tau}$. The latter term depends on wages and prices of material inputs relative to price of output, $w_i / p_{i,k}$ and $m_{i,k} / p_{i,k}$, with the extent of the relationship governed by intensities of labor and input use relative to land.

Fixed costs are investments in units of nonagriculture bundle, with price index P_i^0. We denote the net rental price of (or net returns to) land by $n_{i,k\tau}^f(\omega)$, as gross rents net of fixed costs,

$$n_{i,k\tau}^f(\omega) = z_{i,k\tau}^f(\omega) h_{i,k\tau} - z_{i,0}^f(\omega) P_i^0 \tag{8}$$

The optimal allocation in every plot $\omega \in f$ maximizes returns to plot ω by selecting among crop-technique pairs (k, τ) or not using the plot for agriculture,

$$\max \left\{ h_{i,k\tau} z_{i,k\tau}^f(\omega) \text{ for all } (k,\tau) \in \mathcal{K} \times T,\ P_i^0 z_{i,0}^f(\omega) \right\}$$

The vector of investment requirement and land productivities, $\mathbf{z}_i^f(\omega) \equiv [z_{i,k\tau}^f(\omega)$ for all $(k,\tau) \in \mathcal{K} \times T,\ z_{i,0}^f(\omega)]$ is randomly drawn across plots $\omega \in f$ from a nested Fréchet distribution,

$$\Pr(\mathbf{z}_i^f(\omega) \leq \mathbf{z}_i^f) = \exp\left\{ -\bar{\phi} \left[\left(\Gamma_0(z_{i,0}^f) \right)^{-\theta_1} + \sum_{k \in \mathcal{K}} \left(\Gamma_k(\mathbf{z}_{i,k}^f) \right)^{-\theta_1} \right] \right\}$$
$$\text{where} \quad \Gamma_0(z_{i,0}^f) = \left(\frac{z_{i,0}^f}{a_{i,0}^f} \right), \quad \Gamma_k(\mathbf{z}_{i,k}^f) = \left[\sum_{\tau \in \mathcal{T}} \left(\frac{z_{i,k\tau}^f}{a_{i,k\tau}^f} \right)^{-\theta_2} \right]^{-\frac{1}{\theta_2}} \text{ for all } k \in \mathcal{K}$$

Here, $\bar{\phi} \equiv \left[\Gamma(1 - 1/\theta_1) \right]^{-\theta_1}$ is a normalization to ensure that $\mathbb{E}[z_{i,0}^f(\omega)] = a_{i,0}^f$, and $\mathbb{E}[z_{i,k\tau}^f(\omega)] = a_{i,k\tau}$. 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, as studied in details in McFadden (1981). We present a detailed derivation in the appendix, and here explain the intuition.

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 techniques within every crop. The larger θ_2 relative to θ_1 is, the larger the correlation between draws are across techniques 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. All together, θ_1 and θ_2 govern the pattern of specialization respectively regarding which crop to grow and with which technique to grow it.

When $\theta_2 > \theta_1 \geq 1$, then 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 techniques within a crop is zero. Then, for example, draws between corn-modern and corn-traditional are equally dissimilar to draws between corn-modern and wheat-traditional. In the other special case, where $\theta_2 \to \infty$, there will be perfect correlation between draws across technologies within a crop. As a result, every crop will be produced using only on technology. [15]

Lastly, we specify the production technology of non-crop goods consisting of nonagriculture and agricultural inputs. Among agricultural inputs, production of processed fertilizer, denoted by $v \in \mathcal{J}$, uses the domestic endowments of raw fertilizers, V_i. The production of other non-crop goods (nonagriculture and non-fertilizer inputs) uses labor. Specifically,

$$Q_{i,g} = \begin{cases} A_{i,v} V_i, & \text{fertilizer, } g = v \\ A_{i,g} N_{i,g}, & \text{nonagriculture \& other agricultural inputs, } g \in \mathcal{O} \cup \mathcal{J}, g \neq v \end{cases} \tag{9}$$

where production features constant returns to scale, and $\{A\}$ is a vector of productivity shifters.

[15] In agriculture-related studies, this one-nest version has been used for Roy-type models in labor markets (Lagakos and Waugh, 2013), and in land allocation problems (Costinot, Donaldson, and Smith, 2016; Sotelo, 2019). In the trade literature, recent applications that allow for correlations are Lashkaripour and Lugovskyy (2018), Romando and Lind (2018). We complement these studies by illustrating how to apply the tools to Roy-type or land-use problems, and in addition we make the nontrivial derivation of productivity distributions conditional on selection.

3.4 Equilibrium

3.4.1 Prices and Expenditures

Let E_n be total expenditure in country n. Price indexes of consumption aggregates $C_{n,g}$, C_n^s, and C_n for all $g \in \mathcal{G} \equiv \mathcal{O} \cup \mathcal{J} \cup \mathcal{K}$, $s = \{0, 1\}$, $n \in \mathcal{N}$ are given by

$$
\begin{aligned}
P_{n,g} &= \Big[\sum_{i \in \mathcal{N}} b_{ni,g} (p_{i,g} d_{ni,g})^{1-\sigma_g} \Big]^{\frac{1}{1-\sigma_g}} && (10) \\
P_n^s &= \begin{cases} P_{n,0}, & \text{if } s = 0 \\ \Big[\sum_{k \in \mathcal{K}} b_{n,k} (P_{n,k})^{1-\kappa} \Big]^{\frac{1}{1-\kappa}}, & \text{if } s = 1 \end{cases} && (11) \\
P_n &= \Big[\sum_{s \in \{0,1\}} b_n^s (E_n / P_n)^{\varepsilon^s - 1} (P_n^s)^{1-\eta} \Big]^{\frac{1}{1-\eta}} && (12)
\end{aligned}
$$

We denote by $\beta_{ni,g}$ the share of expenditure by country n on good $g \in \mathcal{G}$ originated from i, by $\beta_{n,k}$ the share of expenditure by country n on crop $k \in \mathcal{K}$ relative to aggregate agriculture expenditure there, and by β_n^s the share of expenditure by country n on sector-level bundles of nonagriculture and agriculture,

$$
\begin{aligned}
\beta_{ni,g} &= \frac{b_{ni,g} (p_{i,g} d_{ni,g})^{1-\sigma_g}}{(P_{n,g})^{1-\sigma_g}} && (13) \\
\beta_{n,k} &= \frac{b_{n,k} (P_{n,k})^{1-\kappa}}{(P_n^1)^{1-\kappa}} && (14) \\
\beta_n^s &= \frac{b_n^s (E_n / P_n)^{\varepsilon^s - 1} (P_n^s)^{1-\eta}}{(P_n)^{1-\eta}} && (15)
\end{aligned}
$$

The price effects operate through substitutions in the upper tier between nonagriculture and agriculture through $(P_n^s / P_n)^{1-\eta}$, in the middle tier between crops within agriculture through $(P_{n,k} / P_n^1)^{1-\kappa}$, and in the lower tier between varieties of different origin countries within a crop 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 with respect to nonagriculture ($s = 0$) and agriculture ($s = 1$) bundles of consumption. Equation (15) shows that expenditure shares β_n^0 and β_n^1 depend on real total expenditure, E_n / P_n. In the empirically relevant case, where $\varepsilon^0 > \varepsilon^1$, a rise in E_n / P_n increases the share of expenditures on nonagriculture.

Our measure of welfare is utility C_n received by total consumption as implicitly defined by equation (3). Our derivation ensures that welfare is given by $C_n = E_n/P_n$. The overall price index, P_n, is itself a function E_n/P_n. Therefore, equation (12) implicitly defines the price index, P_n, to be solved at any level of income and sector-level prices. The pair of equations (12) and (15) characterize the non-homotheticity in demand, i.e. how the price index and expenditure shares change by income.

3.4.2 Output and Resource Allocation

For every field f, we denote the fraction of land allocated to crop-technique (k, τ) by $\pi^f_{ni,k}$. Further, 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 technique τ. The land shares are given by

$$\pi^f_{i,k\tau} = \alpha^f_{i,k} \times \alpha^f_{i,k\tau} \tag{16}$$

where

$$\alpha^f_{i,k\tau} = \frac{\left(a^f_{i,k\tau} h_{i,k\tau}\right)^{\theta_2}}{(H^f_{i,k})^{\theta_2}} \tag{17}$$

$$\alpha^f_{i,k} = \frac{(H^f_{i,k})^{\theta_1}}{(a^f_{i,0} P^0_i)^{\theta_1} + \sum_{k \in \mathcal{K}} (H^f_{i,k})^{\theta_1}} \tag{18}$$

Here, $h_{i,k\tau}$ is the price-inclusive component of returns to crop-technique pair (k, τ), given by equation (7), and aggregate returns to crop k, $H^f_{i,k}$, equals

$$H^f_{i,k} = \left[\sum_{\tau \in \mathcal{T}} \left(a^f_{i,k\tau} h_{i,k\tau}\right)^{\theta_2}\right]^{\frac{1}{\theta_2}} \tag{19}$$

Equations (16)–(19) connect the dispersion parameters of the Fréchet distribution to elasticities of land use. Specifically, θ_2 appears as the elasticity of substitution across techniques within a crop choice, and θ_1 as the elasticity of substitution in land use across crops (and no agriculture). The opportunity cost of agriculture production, $a^f_{i,0} P^0_i$, pins down the 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 technique τ rises in average returns to technique 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-technique (k,τ) is optimally allocated. Conditional on optimal selections, the average productivity of crop-technique (k,τ) in field f equals

$$\mathbb{E}[z^f_{i,k\tau}(\omega) \mid \omega \in \Omega^f_{i,k\tau}] = a^f_{i,k\tau}(\alpha^f_{i,k})^{-\frac{1}{\theta_1}}(\alpha^f_{i,k\tau})^{-\frac{1}{\theta_2}} \tag{20}$$

The conditional mean productivity of crop-technique (k,τ), given by equation (20), is greater than the unconditional mean productivity, $\mathbb{E}[z^f_{i,k\tau}(\omega)] = a^f_{i,k\tau}$, due to the selection of a crop-technique pair (k,τ) if its productivity draw is sufficiently large. A higher share of land is allocated to crop k if returns to crop k, $H^f_{i,k}$, rise relative to those of other crops and opportunity cost of agriculture. This margin of adjustment, governed by θ_1, determines the pattern of specialization across crops.

In addition, conditional on selecting crop k, higher returns to technique τ, $a^f_{i,k\tau}h_{i,k\tau}$, increase the share of land for which technique τ is adopted among the competing techniques to produce crop k. Using equation (7) and equation 17, the relative share of modern to traditional technique, conditional on producing crop k, satisfies

$$\left(\frac{\alpha^f_{i,k1}}{\alpha^f_{i,k0}}\right) = \left[\underbrace{\frac{a^f_{i,k1}}{a^f_{i,k0}}}_{\text{relative avg productivity}} \quad \underbrace{\frac{(w_i/p_{i,k})^{-\gamma^N_{k1}/\gamma^L_{k1}}(m_{i,k}/p_{i,k})^{-\gamma^M_{k1}/\gamma^L_{k1}}}{(w_i/p_{i,k})^{-\gamma^N_{k0}/\gamma^L_{k0}}(m_{i,k}/p_{i,k})^{-\gamma^M_{k0}/\gamma^L_{k0}}}}_{\text{relative input price}} \right]^{\theta_2}.$$

The term in the brackets equals the unconditional expected return of modern technique relative to traditional, which rises when productivity of modern technique rises on average relative to traditional, and when relative prices of inputs fall. The extent to which these changes imply a change in relative land share of modern technique is governed by θ_2. The larger θ_2 is, the greater the extent of adopting modern technique in response to changes in relative productivities and input prices.

Discrete choices of crop-technique pairs for every plot ω implies that

$$Q^f_{i,k\tau}(\omega) = \begin{cases} (\gamma^L_{k\tau})^{-1}\widetilde{h}_{i,k\tau}z^f_{i,k\tau}(\omega), & \omega \in \Omega^f_{i,k\tau} \\ 0, & \omega \notin \Omega_{i,k\tau} \end{cases} \tag{21}$$

The optimal allocation requires each plot $\omega \in f$ either not to be used for agriculture or fully used for the production of one crop using one technique. In addition, returns to land in plot

ω, $h_{i,k\tau} z^f_{i,k\tau}(\omega)$, are only a fraction $\gamma^L_{k\tau}$ of output, with the other fraction paid to labor and material inputs. Aggregate output of crop k using technique 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 per plot, $\mathbb{E}[Q^f_{i,k\tau}(\omega) \mid \omega \in \Omega^f_{i,k\tau}]$. Using equations (16), (20), (21),

$$\begin{aligned} Q^f_{i,k\tau} &= \pi^f_{i,k\tau} L^f_i \times \mathbb{E}\left[Q^f_{i,k\tau}(\omega) \mid \omega \in \Omega^f_{i,k\tau}\right] \\ &= L^f_i (\gamma^L_{k\tau})^{-1} \widetilde{h}_{i,k\tau} a^f_{i,k\tau} (\alpha^f_{i,k})^{\frac{\theta_1 - 1}{\theta_1}} (\alpha^f_{i,k\tau})^{\frac{\theta_2 - 1}{\theta_2}} \end{aligned} \tag{22}$$

Aggregate output of crop k in country i is then the sum across techniques and fields there,

$$Q_{i,k} = \sum_{f \in \mathcal{F}_i} \sum_{\tau \in \mathcal{T}} Q^f_{i,k\tau} \tag{23}$$

Aggregate quantity of nonagriculture good required for fixed costs of setting up plots, is denoted by S_i, and equals

$$S_i = \sum_{f \in \mathcal{F}_i} L^f_i a^f_{i,0} \left[1 - \left(1 - \sum_{k \in \mathcal{K}} \alpha^f_{i,k}\right)^{(\theta_1 - 1)/\theta_1}\right] \tag{24}$$

3.4.3 Market Clearing and General Equilibrium

Labor market clearing in every country $i \in \mathcal{N}$ requires labor supply N_i to equal labor demand from production of nonagriculture, non-fertilizer agricultural inputs, and crops,

$$w_i N_i = \sum_{g \in \mathcal{O} \cup \mathcal{J}, g \neq v} p_{i,g} Q_{i,g} + \sum_{k \in \mathcal{K}} \sum_{f \in \mathcal{F}_i} \sum_{\tau \in \mathcal{T}} \gamma^N_{k\tau} p_{i,k} Q^f_{i,k\tau} \tag{25}$$

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

$$p_{i,0} Q_{i,0} = \sum_{n \in \mathcal{N}} \beta_{ni,0} \beta^0_n E_n + P^0_i S_i \tag{26}$$

$$p_{i,j} Q_{i,j} = \sum_{f \in \mathcal{F}_i} \sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{K}} \beta_{ni,j} \lambda^j_k \gamma^M_{k1} p_{n,k} Q^f_{n,k1} \tag{27}$$

$$p_{i,k} Q_{i,k} = \sum_{n \in \mathcal{N}} \beta_{ni,k} \beta_{n,k} \beta^1_n E_n \tag{28}$$

Finally, by national accounting of flows total expenditure in country i, E_i, equals the sum of factor rewards and trade deficits,

$$E_i = \sum_{k\in\mathcal{K}} \sum_{f\in\mathcal{F}_i} \sum_{\tau\in\mathcal{T}} (\gamma^N_{k\tau} + \gamma^L_{k\tau}) p_{i,k} Q^f_{i,k\tau} - P^0_i S_i + \sum_{g\in\mathcal{O}\cup\mathcal{J}} p_{i,g} Q_{i,g} + D_i \tag{29}$$

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, and the fourth term is trade deficits. Equations 25-29 guarantee that trade deficits sum up to zero, $\sum_{i\in\mathcal{N}} D_i = 0$, and land market clearing condition holds.

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

Definition. For all countries $n, i \in \mathcal{N}$, fields $f \in \mathcal{F}_n$, goods $g \in \mathcal{G}$ consisting of nonagriculture, agricultural inputs $j \in \mathcal{J}$, and crops $k \in \mathcal{K}$, sectors $s \in \{0, 1\}$, and techniques $\tau \in \mathcal{T}$, a **global economy** is characterized by

- Endowments $\mathcal{E} \equiv \{L^f_n, N_n, V_n, D_n\}$;
- Production elasticity parameters $\Theta_{\mathcal{A}} \equiv \{\theta_1, \theta_2\}$;
- Consumption elasticity parameters $\Theta_{\mathcal{B}} \equiv \{\varepsilon^0, \varepsilon^1, \eta, \kappa, \sigma_g\}$;
- Production shifters $\mathcal{A} = \{\gamma^L_{k\tau}, \gamma^M_{k\tau}, \gamma^N_{k\tau}, \lambda^j_k, a^f_{n,0}, a^f_{n,k\tau}, A_{n,g}\}$;
- Consumption shifters $\mathcal{B} = \{b^s_n, b_{n,k}, b_{ni,g}, d_{ni,g}\}$

Definition. Given a global economy characterized by $\{\mathcal{E}, \mathcal{A}, \mathcal{B}, \Theta_{\mathcal{A}}, \Theta_{\mathcal{B}}\}$, a **general equilibrium** consists of prices $\{p_{n,g}\}$ for all $n \in \mathcal{N}$, $g \in \mathcal{G}$ such that equations 7–29 hold.

3.5 Discussion: Recasting the micro to macro problem

We show that aggregate prediction quantities predicted by our model can be replicated by an alternative problem in which producers choose aggregate levels of land use subject to certain possibility frontiers. Here, by an aggregate unit we mean to refer to a field. In our model, field-level variables are the aggregation of discrete choices across plots within field. We present a field-level maximization problem that replicates the exact field-level predictions of our model. Holding field f in country i fixed, this aggregate problem is given by:

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

$$\text{subject to} \quad \left[\sum_{\tau\in\mathcal{T}} (\widetilde{L}^f_{i,k\tau}/a^f_{i,k\tau})^{\frac{\theta_2}{\theta_2-1}}\right]^{\frac{\theta_2-1}{\theta_2}} \leq \widetilde{L}^f_{i,k} \tag{30}$$

$$\left[\sum_{k\in\mathcal{K}} (\widetilde{L}^f_{i,k})^{\frac{\theta_1}{\theta_1-1}}\right]^{\frac{\theta_1-1}{\theta_1}} \leq L^f_i \tag{31}$$

Here, $\widetilde{L}^f_{i,k\tau}$ and $\widetilde{L}^f_{i,k}$ are efficiency units of land at the level of crop-technique $k\tau$ and crop k.[16] The producer maximizes the sum of returns across uses of land given price-inclusive term $h_{i,k\tau}$ described by equation (7), technology coefficients $a^f_{i,k\tau}$, and endowment L^f_i.[17]

We illustrate this problem with diagrams for two crops, which we call rice and wheat, each can be produced using traditional or modern techniques. To save on notation, we drop country and field indicators. The production possibility frontiers are represented in two tiers. The lower tier reflects substitution possibilities across techniques within a crop, and the upper tier disciplines substitution possibilities between crops. Figure 5 illustrates the frontier along the dimension of technology within a crop (Panel a), and between crops (Panel b).

In Panel (a), we show for every crop k the optimal choices of output in units of land efficiency that are produced using traditional ($\tau = 0$) and modern ($\tau = 1$) techniques. The maximum that could be achieved if all resources for the production of crop k was 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, $\widetilde{L}_k$, that is a choice variable in the upper tier. The slope of the frontier curve at point $(\widetilde{L}_{k0}, \widetilde{L}_{k1})$ is proportional to $(\widetilde{L}_{k0}/\widetilde{L}_{k1})^{1/(\theta_2-1)}$, governed by $\theta_2 \in (1,\infty)$. The smaller θ_2, the greater the curvature, the more elastic choices of technology for a given 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

[16] 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 (7), $\widetilde{h}_{i,k\tau} = (w_i/p_{i,k})^{-\gamma^N_{k\tau}/\gamma^L_{k\tau}}(m_{i,k}/p_{i,k})^{-\gamma^M_{k\tau}/\gamma^L_{k\tau}}$ is the effective relative input price.

[17] For the sake of exposition, here we have set the value of outside option at zero.

[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 are 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.

by relative labor and input intensities.

In Panel (b), we show 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 $\theta_1 \in (1, \infty)$. A smaller θ_1 means a greater curvature, hence a larger sensitivity in substitution across crops if relative prices change.[19] In addition, the slope of the iso-value line is given by $(-H_{rice}/H_{wheat})$. Reproducing H_k from equation (19), it is a generalized mean 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 area of land. 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.

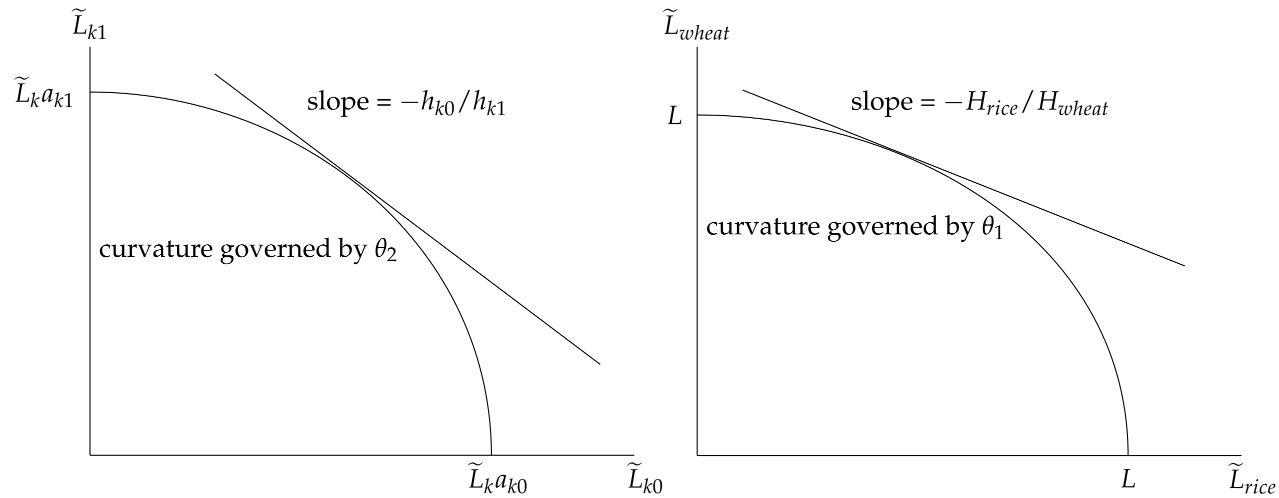
Lastly, it is remarkable that shadow prices of this aggregate problem replicate land rents predicted by our micro-founded model. Specifically, we derive in the appendix that the Lagrange multiplier associated with the slack constraints (30) and (31) are respectively given by H_k and $[\sum_k H_k^{\theta_1}]^{1/\theta_1}$. That is, the shadow price of the land allocated to crop k is H_k, which is the average returns to land used for production of crop k, and the shadow price of the entire cropland is given by $[\sum_k H_k^{\theta_1}]^{1/\theta_1}$, which is precisely the average rents of cropland.[20]

[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.

[20] For more details and full derivations for this aggregate problem, see Appendix (C.6).

Figure 5: Production Possibility Frontier

a. Between techniques within crop k b. Between crops



Notes: Panel (a) shows the lower-tier production possibility frontier within crop k between two technologies, 1 as modern and 0 as traditional. Panel (b) shows the upper-tier production possibility frontier between two crops. $\{\widetilde{L}_{k\tau}, \widetilde{L}_k\}$ 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 L.

4 Taking the Model to Data

In this section, we take the model to data. Our quantification of the model combines calibration and estimation and can be divided into two major steps. First, we follow standard practices in the literature to estimate parameters in the demand side. Second, we use the method of moments to estimate the production side.

4.1 Step 1: Demand side

We estimate or borrow from the literature the following demand side parameters: the elasticity of substitution across crops (κ), the elasticity of substitution across varieties of a good (σ_g), the elasticity of substitution between agricultural and non-agricultural bundle of goods (η), and the income elasticity with respect to agriculture and non-agriculture (ε^s). With estimates of κ, σ_g and η, we use expenditure data to recover demand shifters $\{b_{ni,g}d_{ni,g}^{1-\sigma_g}, b_{n,k}\}$. In addition, we recover the expenditure shifters associated with the consumption of agriculture and non-agriculture goods, b_n^s, after constructing model-implied sectoral price indexes.

As in Costinot, Donaldson, and Smith (2016), we estimate the elasticity of substitution between crops (σ_k) based on the following gravity-type equation,

$$\log\left(\frac{X_{ni,k}}{X_{n,k}}\right) = \delta_{n,k} + (1-\sigma_k)\log p_{i,k} + \epsilon_{ni,k}, \tag{32}$$

where $\delta_{n,k} \equiv -\log[\sum_i b_{ni,k}(p_{i,k}d_{ni,k})^{1-\sigma_k}]$, $\epsilon_{ni,k} = \log b_{ni,k}d_{ni,k}^{1-\sigma_k}$, $X_{ni,k}$ is the purchases of n from country i of crop k and $X_{n,k}$ is total purchases of country n on crop k. Without loss of generality we set $\sum_{i=1}^N \epsilon_{ni,k} = 0$.[21] Due to potential correlations between demand shocks $\epsilon_{ni,k}$ and prices $\log p_{n,k}$, we instrument $\log p_{i,k}$ with the average agricultural suitability of the exporting country, using FAO-GAEZ data. With our estimate of σ, we recover the demand shifters with respect to crops from the residuals of equation (32) and construct the country-level price index of every crop $P_{n,k}$. With this price index in hand, we take logs of equation (14) and estimate κ based on

$$\log\left(\frac{X_{n,k}}{X_n^1}\right) = \delta_n + (1-\kappa)\log P_{n,k} + \epsilon_{n,k} \tag{33}$$

where $\epsilon_{n,k} = \log b_{n,k}$, $\sum_{k\in\mathcal{K}} \epsilon_{n,k} = 0$ and X_n^1 is aggregate purchases of all crops. To address the endogeneity of $\log P_{n,k}$, we instrument the price index using the average agricultural suitability of each country.

For non-agricultural goods, we set the elasticity of substitution to $\sigma_g = 4$ according to the literature (see Simonovska and Waugh (2014)), and use two different procedures to collect the demand shifters depending on whether producer prices are available or not. For the case of fertilizers $g = v$, we have data on producer prices and collect the residuals from the following equation

$$\log\left(\frac{X_{ni,v}}{X_{n,v}}\right) - (1-\sigma_v)\log p_{i,v} = \delta_{n,v} + \epsilon_{ni,v}. \tag{34}$$

For the remaining non-agricultural goods (pesticides, farm machinery and non-agriculture good), we do not have data on producer prices. Therefore, we collect the residuals from

$$\log\left(\frac{X_{ni,g}}{X_{n,g}}\right) - (1-\sigma_g)\log w_{i,g} = \delta_{n,g} + \delta_{i,g} + \epsilon_{ni,g}, \tag{35}$$

[21] Note that trade costs and demand shifters are both included in the error term $\epsilon_{ni,g}$.

where w_i is the value added per worker in country i and $\delta_{i,g}$ is a fixed effect that captures the factor productivity of country i. Note that here we use our assumption that the production of non-agricultural goods is constant returns to scale and employs only labor.

Finally, as for the upper tier demand elasticities, we set income elasticities at $\varepsilon^0 = 1.5$ and $\varepsilon^1 = 0.5$, and the substitution elasticity at $\eta = 0.5$ in line with the estimates of Comin, Lashkari, and Mestieri (2015). These parameters imply that agriculture is a necessity good whereas nonagriculture is a luxury, and that agriculture and nonagriculture are complements in consumption. In the next step, we quantify the supply side of the economy conditional on sectoral expenditures where we obtain price indices of nonagriculture P_n^0 and agriculture (P_n^1). We then use these model-implied price indices to recover expenditure shifters in the upper tier of demand (b_n^0 and b_n^1).

In this step, we obtain demand elasticities $\Theta_{\mathcal{B}}$ and demand shifters $\mathcal{B}$. Our next step will be conditional on $(\Theta_{\mathcal{B}}, \mathcal{B})$.

4.2 Step 2: Supply side

In this step, we quantify the following supply side parameters: total factor productivity of non-agriculture sector $A_{n,0}$, cost shares of agricultural inputs in modern and traditional technology ($\gamma_{k\tau}^L, \gamma_{k\tau}^N, \gamma_{k\tau}^M$ and λ_k^j), the dispersion of productivities across crops θ_1 and within crops across technologies θ_2, the total factor productivity of the land in each field and technology $a_{i,k\tau}^f$, and the investment parameter $a_{n,0}^f$. Our procedure consists of three parts. First, we recover total factor productivity of goods $A_{n,g}$ from the origin fixed effect in equation (35) and calibrate our cost share parameters ($\gamma_{k\tau}^L, \gamma_{k\tau}^N, \gamma_{k\tau}^M$ and λ_k^j) using data on costs of production from the US. Second, we set up a calibration problem in which we calibrate the field-level average land productivities ($a_{i,k\tau}^f$) and the investment parameter ($a_{n,0}^f$) given (θ_1, θ_2). Third, we estimate (θ_1, θ_2) via GMM subject to the calibration problem.

Calibration Problem

Factor Shares. We set the factor shares in the agricultural production function using a few data sources together with equations implied by our model. Since the traditional technique uses no material input, we set $\gamma_{k0}^M = 0$. Due to data limitations, we make the assumption that factor shares of land, labor, and material inputs for every technology, $\gamma_{k\tau}^L, \gamma_{k\tau}^N, \gamma_{k\tau}^M$ are common across crops. In addition, with an approximation, our model implies that

$$(\gamma_0^L/\gamma_1^L) = \frac{(\bar{\gamma}_j^M \widetilde{\alpha}_j) - (\bar{\gamma}_i^M \widetilde{\alpha}_i)}{\bar{\gamma}_j^M - \bar{\gamma}_i^M}$$

where i and j refer to any two countries, $\widetilde{\alpha}_i = (1 - \bar{\alpha}_{i,1})/\bar{\alpha}_{i,1}$ is relative share of traditional to modern technology at the aggregate in country i, and $\bar{\gamma}_i^M$ is the aggregate cost share of intermediate inputs in country i. Using data for these aggregate variables for the United States and Brazil, we calibrate the factor share of land in traditional relative to modern technology, γ_0^L/γ_1^L. In addition to $\bar{\gamma}_{USA}^M$, we collect data from the USDA Commodity Costs and Returns aggregate cost shares of land $\bar{\gamma}_{USA}^L$ and of labor $\bar{\gamma}_{USA}^L$, which we use together with factor share of land to recover all factor shares. We also obtain the cost share of fertilizers, pesticides, and farm machinery across crops from USDA Commodity Costs and Returns. Table (A.2) reports the factor shares, $(\gamma_\tau^L, \gamma_\tau^N, \gamma_\tau^M)_\tau$ and the median of λ_k^j across crops for the three categories j of agricultural inputs.

Calibration Targets. Given demand elasticities and shifters $(\Theta_{\mathcal{B}}, \mathcal{B})$, and the intensity parameters $(\gamma_{k\tau}^L, \gamma_{k\tau}^M, \gamma_{k\tau}^N, \lambda_k^j)$, conditional on production elasticities $\Theta_{\mathcal{A}} = (\theta_1, \theta_2)$, we want to choose $(a_{n,0}^f, a_{n,k\tau}^f)$ such that all equilibrium relationships hold, and the model exactly matches three sets of calibration targets which we explain below.[22]

As discussed earlier, data on potential yields are not direct measures of average land productivities ($a_{i,k\tau}^f$). Here, we propose a method to calibrate these productivities using data on potential yields in a way that is theoretically consistent with our framework. Let $y_{i,k\tau}^{f,FAO}$ denote the potential yield in FAO-GAEZ data. By definition $y_{i,k\tau}^{f,FAO}$ is the average yield of crop k using technique τ if the entire field f was allocated to crop-technique (k, τ). Using this definition, we find the model prediction of potential yields. Specifically, equation (22), when evaluated at $\alpha_{i,k}^f = \alpha_{i,k\tau}^f = 1$, gives the output of crop-technique (k, τ) if the entire field was allocated to (k, τ). Dividing the resulting amount of output by the entire land area delivers $(\gamma_{k\tau}^L)^{-1} \widetilde{h}_{ik\tau} a_{i,k\tau}^f$ as the model prediction of potential yield. Here, $\widetilde{h}_{ik\tau}$ captures the effect of local prices in shaping land productivity. In contrast, measures of potential yield in FAO-GAEZ data are meant *not* to reflect local market conditions. Precisely for this reason, as in Sotelo (2019), we attribute measures from FAO-GAEZ data as consistent with optimal input choices given a vector of global prices. Consequently, to connect our model to potential yield

[22] This procedure is computationally intensive, and results in this section are currently based on five percent sample of fields randomly drawn for each country. We will update our results for the full sample.

data, we require that

$$y_{i,k\tau}^{f,FAO} = (\gamma_{k\tau}^{L})^{-1}\widetilde{h}_{k\tau}^{FAO} a_{i,k\tau}^{f}$$

where $\widetilde{h}_{k\tau}^{FAO}$ is consistent with some vector of global prices. This relationship implies that:

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

where $\delta_{k\tau} \equiv \gamma_{k\tau}^{L} / \widetilde{h}_{k\tau}^{FAO}$ is an unobserved term that connects observed potential yields $y_{i,k\tau}^{f,FAO}$ to average land productivities $a_{i,k\tau}^{f}$ in our model. Consistent with the construction of the potential yield data, we restrict $\delta_{k\tau}$ to be a global parameter that does not vary across fields or countries. That is, for every crop-technology pair we require to adjust the *scale* of observed potential yields *globally* to obtain model-consistent land productivity shifters $a_{i,k\tau}^{f}$.

To pin down the resulting $2 \times K$ adjustment shifters, we consider two calibration targets: $\bar{Q}_{USA,k}$ as the supply quantity of every crop k in the USA, and $\bar{\alpha}_{USA,k1}$ as the aggregate share of agricultural land in the USA allocated to modern technology for every crop k. It is instructive to write $\delta_{k\tau}$ as

$$\delta_{k\tau} = \begin{cases} d_k^0 & , \tau = 0 \\ d_k^1 d_k^0 & , \tau = 1 \end{cases}$$

The first calibration target, $\{\bar{Q}_{USA,k}\}_k$, pins down the common scale of adjustment parameters, d_k^0, and the second calibration target, $\{\bar{\alpha}_{USA,k}\}_k$, pins down the extra adjustment parameter of modern technique, d_k^1. As such, when the model under-predicts aggregate supply quantity of crop k in the USA, $\bar{Q}_{USA,k}$, we want to increase the common scalar d_k^0; and, when the model under-predicts the share of aggregate share of land allocated to modern technology in the USA, $\bar{\alpha}_{USA,k1}$, we want to increase the adjustment parameter that governs the premium for modern technique, d_k^1.

As our third and final set of calibration target, we adjust the investment intensity parameter $a_{n,0}^{f}$ to match field-level data on the share of cropland, $\{\bar{\alpha}_n^f\}$, as reported in EarthStat.

In the calibration problem, we require our model to be in equilibrium subject to a set of constraints by which the model has to match the three above-mentioned sets of calibration targets. Computationally, we use a nested fixed point algorithm to conduct this calibration problem. In the inner loop, we solve for equilibrium prices given expenditure on agriculture and nonagriculture sectors in every country. In the outer loop we solve for $\{a_{i,k\tau}^{f}, a_{i,0}^{f}\}$ by fitting the model to the calibration targets. To make the exposition more accessible as move to the estimation, we represent the entire calibration problem as

$$\mathbf{c}(\theta_1, \theta_2) = 0$$

where $\mathbf{c}$ is a set of constrains requiring that the model is in equilibrium and it fits the calibration targets.

Estimation

We estimate the dispersion in land productivities $\Theta_{\mathcal{A}} = (\theta_1, \theta_2)$ using the generalized method of moment conditional on the calibration problem defined by $\mathbf{c}(\Theta_{\mathcal{A}}) = 0$. Our estimation is based on two sets of moments. Each set of moments is closely related to the identification of one of the dispersion parameters.

Our first moment is based on model predictions for yields and observed yields in the United States. Let $\hat{y}_{i,k}^{f}$ be the observed yield of crop k in field f in country i. Allowing for mismeasurements in the yield data,

$$y_{i,k}^{f} = \hat{y}_{i,k}^{f} \epsilon_{i,k}^{f},$$

where $y_{i,k}^{f}$ is the true value, and $\epsilon_{i,k}^{f}$ is the error term. We assume that predicted deviations from the observed log yield are orthogonal to log land shares, $\mathbb{E}[\ln \epsilon_{i,k}^{f} \times \ln \alpha_{i,k}^{f}] = 0$. Here we are constructing this moment across fields within the United States. The underlying identification assumption is that land shares are sufficient statistic for model predictions of yields. That is, model deviations from observed yields cannot be systematically explained by model predictions of land shares. This moment condition is tightly related to the identification of θ_1 and we define the resulting moment as m_1.

Our second set of moments is based on cost shares of agricultural inputs across countries. As we presented the empirical pattern 2, countries with a higher GDP per capita have systematically higher cost shares of agricultural inputs (Fig. 3) A model with a Cobb-Douglas technology that does not have country-specific parameters, however, forces all countries to have the same cost share of inputs. In our model, instead, we have two technologies, and the elasticity of substitution between technologies, θ_2, controls how responsive agricultural producers are to relative wages and input prices. Higher wages and lower input prices induces agricultural producers to shift toward modern technologies, which raises the share of input costs in agriculture. If θ_2 is large, the model generates larger differences in aggregate costs shares of agricultural inputs across low-income and high-income countries. Alternatively, if θ_2 approaches to 1, then the cost share of inputs across countries will be negligible.

Given this intuition, we construct moment conditions that are informative about differences between cost share of agricultural inputs in low-income and high-income countries. Our second and third moment conditions are the mean cost share of agricultural inputs in the two upper deciles and the two lower decides of income per capita across countries. We call these moments m_2 and m_3. These two moments are closely related to the identification of θ_2.

Stacking the moment conditions, we have $g(\Theta_{\mathcal{A}}) = [m_1(\Theta_{\mathcal{A}}), m_2\Theta_{\mathcal{A}}, m_2\Theta_{\mathcal{A}}] - [\widehat{m}_1, \widehat{m}_2, \widehat{m}_3]$. We therefore base our estimation procedure on the moment condition

$$\mathbb{E}(g(\Theta_{\mathcal{A}})) = 0$$

We seek values of $\widehat{\Theta}_{\mathcal{A}} = (\widehat{\theta}_1, \widehat{\theta}_2)$ that achieves

$$\begin{aligned} &\widehat{\Theta}_{\mathcal{A}} = \arg\min_{\Theta_{\mathcal{A}}} \; g(\Theta_{\mathcal{A}})g(\Theta_{\mathcal{A}})' \\ &\text{subject to} \quad \mathbf{c}(\Theta_{\mathcal{A}}) = 0. \end{aligned}$$

4.3 Estimation Results

Table 3 presents results from the estimation of the model. On the demand side, we have estimated the elasticity of substitution for crops across supplying countries, σ at 6.89 and the elasticity of substitution across crops at 3.31. We have taken the rest of demand elasticities from the literature, as explained in Section 4.1.

On the supply side, our estimation implies a production elasticity of substitution across crops, θ_1, equal to 2.05, and a production elasticity of substitution across technologies within a crop, θ_2, equal to 4.38. Our estimate of θ_1 is in the ballpark of the literature. Using variations in crop outputs across countries, Costinot, Donaldson, and Smith (2016) estimate this elasticity at 2.6. Using variations in land shares and prices across regions within Peru, Sotelo (2019) estimate this elasticity at 1.6. Using farm-level data from Uganda, Bergquist, Faber, Fally, Hoelzlein, Miguel, and Rodriguez-Clare (2019) estimate a range of elasticities between 1.8 and 2.9. To the best of our knowledge there is no study in the literature that estimates an elasticity similar to θ_2, so we do not have a reference for comparison. Our estimates however

Table 3: Estimation of the Model

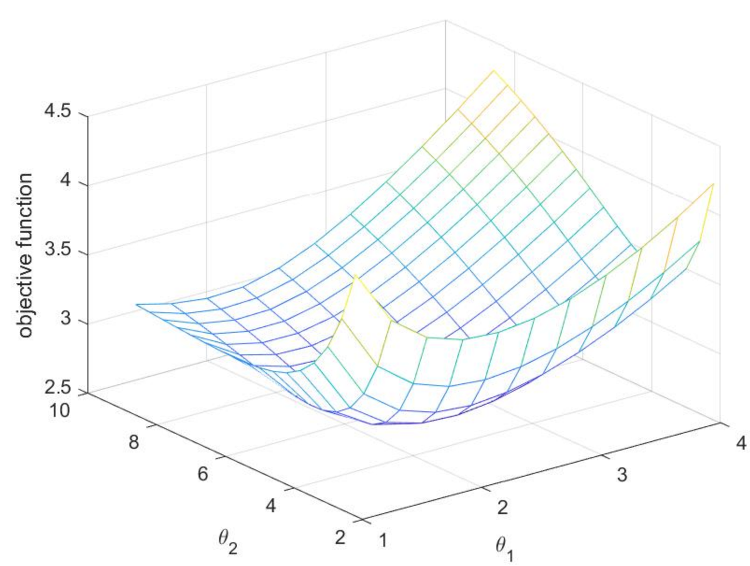
Description	Parameter	Method	Value
A. Demand Side			
- Elast of subst across origins in agriculture	σ	IV	6.89
- Elast of subst across crops	κ	IV	3.31
B. Supply Side			
- Productivity dispersion between crops	θ_1	GMM	2.05
- Productivity dispersion between technologies	θ_2	GMM	4.38

Notes: This table shows estimation results for the demand side and the supply side. See Section 4.1 and 4.2 for the details on our estimation procedure.

imply that agricultural producers are more responsive in substituting between technologies within a choice of crops, than substituting between crops.

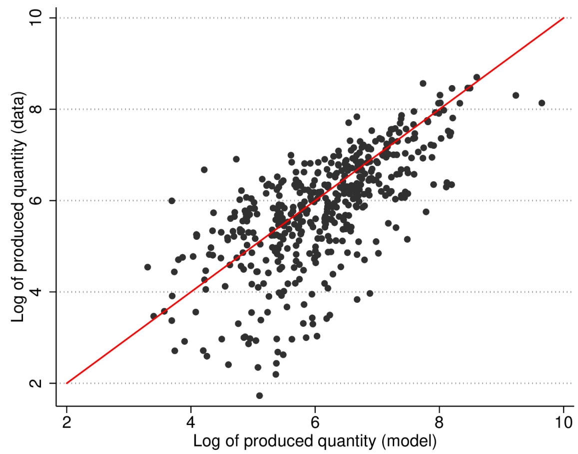
To illustrate the identification of θ_1 and θ_2, we conduct a grid search exercise. Specifically, we show in Figure 6 the surface of our GMM objective function evaluated at a wide range of (θ_1, θ_2). The figure demonstrates a concave function around the estimated parameters that are also the *global* minimum.

Figure 6: Identification of Productivity Dispersion Parameters (θ_1 and θ_2).



Notes: This figure shows the objective function of the GMM procedure used to estimate θ_1 and θ_2, where θ_1 captures the dispersion of productivities between crops and θ_2 captures the dispersion of productivities between technologies within a crop. The values at which the objective function is minimized are $\theta_1 = 2.05$ and $\theta_2 = 4.38$.

Figure 7: Fit of the Model for Crop Output



Notes: This figure shows the model fit of crop outputs at the level of countries. The red line shows the 45 degree line. Both variables are represented in log10. Each data point represents a country-crop pair.

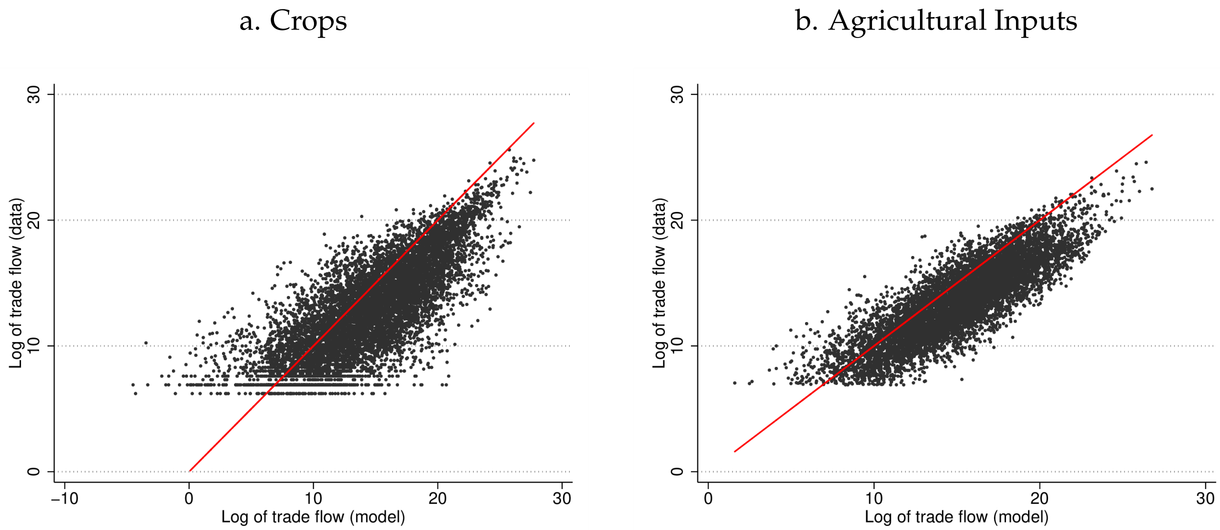
4.4 Goodness of Fit

We have a rare opportunity in this paper to use data on field-level potential yields as productivity shifters rather than treating them as residuals. In other words, we let our model fail to fit the baseline data on agricultural production and by doing so, we can have a sense of how our our estimated model perform with respect to in-sample and out-of-sample data. Hence, before we use our model for quantitative analysis, we examine our model goodness of fit. Specifically, we report the model fit with respect to several variables including production and employment in agriculture.

Figure 7 compares the log quantity of crop outputs at the level of countries predicted by the model versus data. In our calibration, we adjusted land productivities ($a^f_{i,k1}$ and $a^f_{i,k0}$) using potential yields from FAO-GAEZ while we used data on production of crops only from the United States. Therefore, the main factors driving the predictions in Figure 7 are our calibrated land productivities as well our estimated elasticities. The model predictions line up reasonably well with respect to observed data. Specifically, a regression of log observed crop quantities against log predicted crop quantities gives a coefficient estimate of 0.82 with $R^2 = 0.47$.

Since we will study how globalization shaped agricultural productivity, we also check if our model matches well trade flows in the data. Figure 8(a) shows the model fit for trade flows in agriculture. Because our model allows for unobserved demand shifters, the reason for why it does not perfectly match data on trade flows is that predicted prices are different

Figure 8: Fit of the Model for Trade Flows



Notes: This figure shows the fit of the model in terms of trade flows. The red line shows the 45 degree line. Both variables are represented in log10. Each data point represents a origin-destination-crop triple in panel a and a origin-destination-input tripe in panel b.

from those in the data. The relationship between predicted versus observed trade flows of crops is positive and strong: a regression of observed trade flows against predicted ones gives a slope of 1.01 with $R^2 = 0.48$. In addition, Figure 8(b) shows the model fit for agricultural inputs. The relationship between predicted and observed trade flows of agricultural inputs is also strong, with a regression that gives a slope of 0.97 with $R^2 = 0.75$.[23]

In addition, we evaluate the model fit with respect to measures of productivity and employment in agriculture across countries. Table 4 presents model predictions versus data on valued added per worker, cost share of agricultural inputs, and agricultural share of labor employment across countries. We classify countries in four quartiles in terms of the data on value added per worker. The model matches reasonably well with the distribution of value added per worker across quartiles (columns 1 to 2). For the cost share of inputs in agriculture, the model matches well the increase in the cost share of inputs observed in countries with higher value added per worker. Cross-country differences in the cost share of inputs imply cross-country variations in agriculture labor intensity, which is in turn consequential for cross-country differences in the labor share of agriculture. Columns 5 and 6 show that the model also matches well with the distribution of labor share in agriculture despite the fact that we do not target this moment.

[23]Figure A.1 in the appendix shows the model fit for trade flows of non-agriculture good. In this case, we find a slope of 0.93 with $R^2 = 0.95$.

Table 4: Fit of the Model according to Quartiles of VA per Worker

Quartile of VA per Worker			Cost Share of Agr Inputs		Labor Share in Agriculture	
Group	Data	Model	Data	Model	Data	Model
(1)	(2)	(3)	(4)	(5)	(6)	
Q1	0.023	0.070	0.085	0.117	0.548	0.422
Q2	0.090	0.183	0.138	0.259	0.268	0.107
Q3	0.291	0.495	0.191	0.347	0.126	0.039
Q4	0.895	1.138	0.348	0.406	0.036	0.013

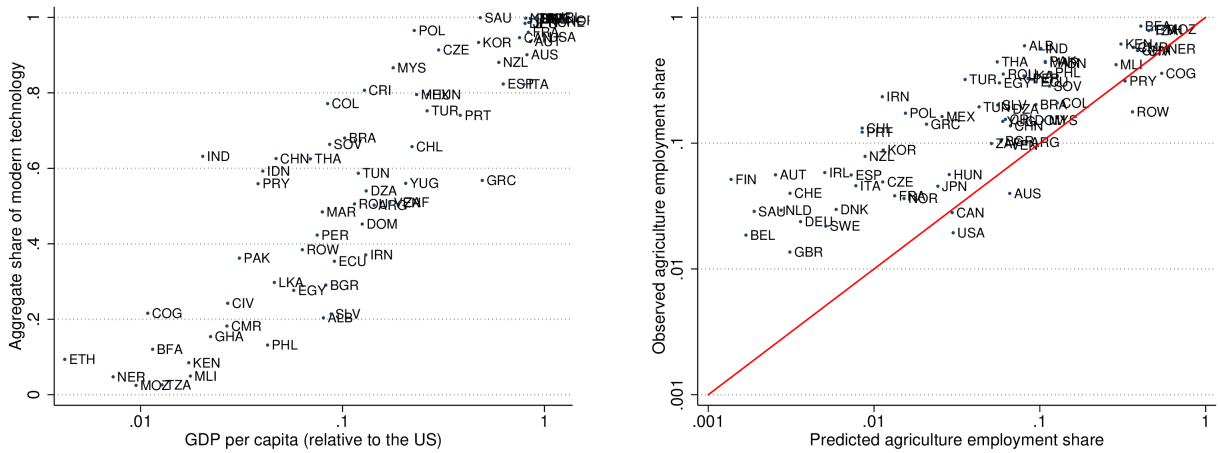
Notes: In this table, we divide countries into four quartiles according to the value added per worker in the data. Value added per worker in column 1 and 2 are relative to the USA.

Finally, we show our model predictions for the extent to which agriculture production depends on modern, labor-saving technologies across countries. Figure 9(a) shows a scatter plot of the aggregate share of land allocated to modern technology across countries against their GDP per capita. The model generates substantial variation in the share of land allocated to modern technologies. Low-income countries such as Ethiopia, Ghana, and Burkina Faso have shares of their land in modern technologies below 20%. Consistent with these predictions, we observe in the data that these countries have extremely low use of fertilizers, pesticides, and farm machinery. The share of land in modern technology is typically in the range of 50% to 80% in middle-income countries such as Brazil, Thailand, and Turkey, and typically around 90% to 100% in high-income countries. Our calibration requires US share to be at 95% in line with our reading of US agriculture data on the use of agricultural inputs, whereas the other points on the scatter plot are predictions of the model. Here, there are two key mechanisms driving these choices. First, since traditional technologies are labor-intensive, low-income countries tend to use traditional technologies due to lower wages. Second, low-income countries due to import barriers typically face higher input prices discouraging a shift toward modern technologies.

Figure 9(b) shows the share of labor employed in agriculture predicted by the model against data. Note that agriculture employment is entirely an out-of-sample variable since we did not target it in our calibration or estimation. Nonetheless, the fit of our model along this dimension is reassuring. There is a clear positive relationship with respect to the data. A regression of observed log labor share against predicted log labor share gives a slope of 0.56 with $R^2 = 0.68$. The slope, however, indicates that our model over-predicts the slope at which log labor share increases across countries.

Figure 9: Model Predictions for Technology and Employment Share

a. Share of Land Allocated to Modern Technology   b. Share of Agricultural Employment



Notes: This figure shows the predictions of the model in terms of the share of land allocated to modern technologies and the share of employment in agriculture.

5 The Impact of Globalization on Agricultural Productivity

This section evaluates the reductions in trade costs between 1980 and 2010 on agricultural productivity around the world.

5.1 Measuring Changes in Trade Costs

To estimate changes to trade costs, we follow a common approach adopted in the gravity literature as described in Head and Mayer (2014). We assume that the trade component of the demand shifters ($d_{ni,g}$) is symmetric and normalize the trade cost of a country with itself to $d_{ii,g} = 1$. In addition, we suppose that trade costs of non-agricultural goods and agricultural inputs are the same. Combining these assumption with our equation for total sales, for $g = 0, 1, ..., J$,

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

where $\epsilon_{in,g} = \log(b_{ni,g}b_{in,g}/b_{ii,g}b_{ni,g})$. We estimate δ_{in} in a fixed effect regression using bilateral trade data in a given year. With values for σ which we have set to 4, we then recover the values of trade costs d_{ni} 2010 and 1980.

Figure A.3 shows the distribution of the change in trade costs between 1980 and 2010. We find an average reduction of trade costs (weighted by trade flows of 2010) of 37%, featuring substantial heterogeneity across countries. For example, while the average import costs in the sub-Saharan Africa fell by 27%, those in Latin America fell by 33% and those in East Europe fell by 60%. This is line with previous estimates in the literature such as Jacks, Meissner, and Novy (2008).

We simulate our model at counterfactual demand shifters implied by our estimated trade costs of 1980. Specifically, let Δ_{ni} be the percentage change in trade cost d_{ni} from 2010 to 1980. We compute the counterfactual demand shifters as $b_{ni,g}(\Delta_{ni}d_{ni})^{(1-\sigma)}$ which we use to simulate our model.

5.2 Globalization in Agricultural Inputs

We now examine the extent to which reductions in trade costs of agricultural inputs affected agricultural productivity and food consumption around the world. The counterfactual nature of this question requires us to disentangle the effect of globalization in agricultural inputs from that of other changes to the world economy. We consider a counterfactual world in which trade costs of agricultural inputs are set to their estimated level in 1980, and compare the resulting equilibrium with that in the baseline of 2010. We emphasize that this is a counterfactual change as we keep trade costs of crops and non-agriculture sector, as well as population and productivities at their baseline value of 2010. Here, we are benefiting from our structural model to focus on the impact of globalization in agricultural inputs when it is separated out from other potential changes.

To illustrate the major channels at work, we report in a few sets of figures a chain of effects from agricultural input prices to agricultural productivity, and from there to consumption and welfare. Specifically, we demonstrate a summary of these results in Figures (10)-(11) as well as Tables (A.4)-(A.5). We present results as changes from the factual scenario (baseline of 2010) to the counterfactual (counterfactual with trade costs of 1980).

As a result of the overall increase in trade costs of agricultural inputs, as shown in Figure A.3, the price index of agricultural inputs at the location of use would rise for many countries. A higher price of inputs makes agricultural producers allocate a larger share of land to traditional technologies in the counterfactual outcome. We show this relationship in

Figure (10). The larger the increase in the price of agricultural inputs, the larger the extent to which land is allocated to traditional technologies in the counterfactual 1980 compared to the baseline 2010. The figure shows this relationship across all countries for corn and wheat, which remain highly representative of this pattern also for other crops.

In addition, we emphasize that due to general equilibrium effects, the agricultural input price index would not necessarily rise for all countries. The overall increase in trade costs reduces global demand for agricultural inputs. Hence, prices of these inputs at the *location of production* would be typically lower in the counterfactual of 1980. If trade costs for a country were sufficiently larger in 1980 compared to 2010, which is the case for many countries, then the price of agricultural inputs at the *location of use* would be higher in the counterfactual of 1980. Otherwise, the price of inputs at the location of use would be lower, and so, the share of land allocated to modern technology would be larger in the counterfactual outcome. We take a moment to explain this interesting channel.

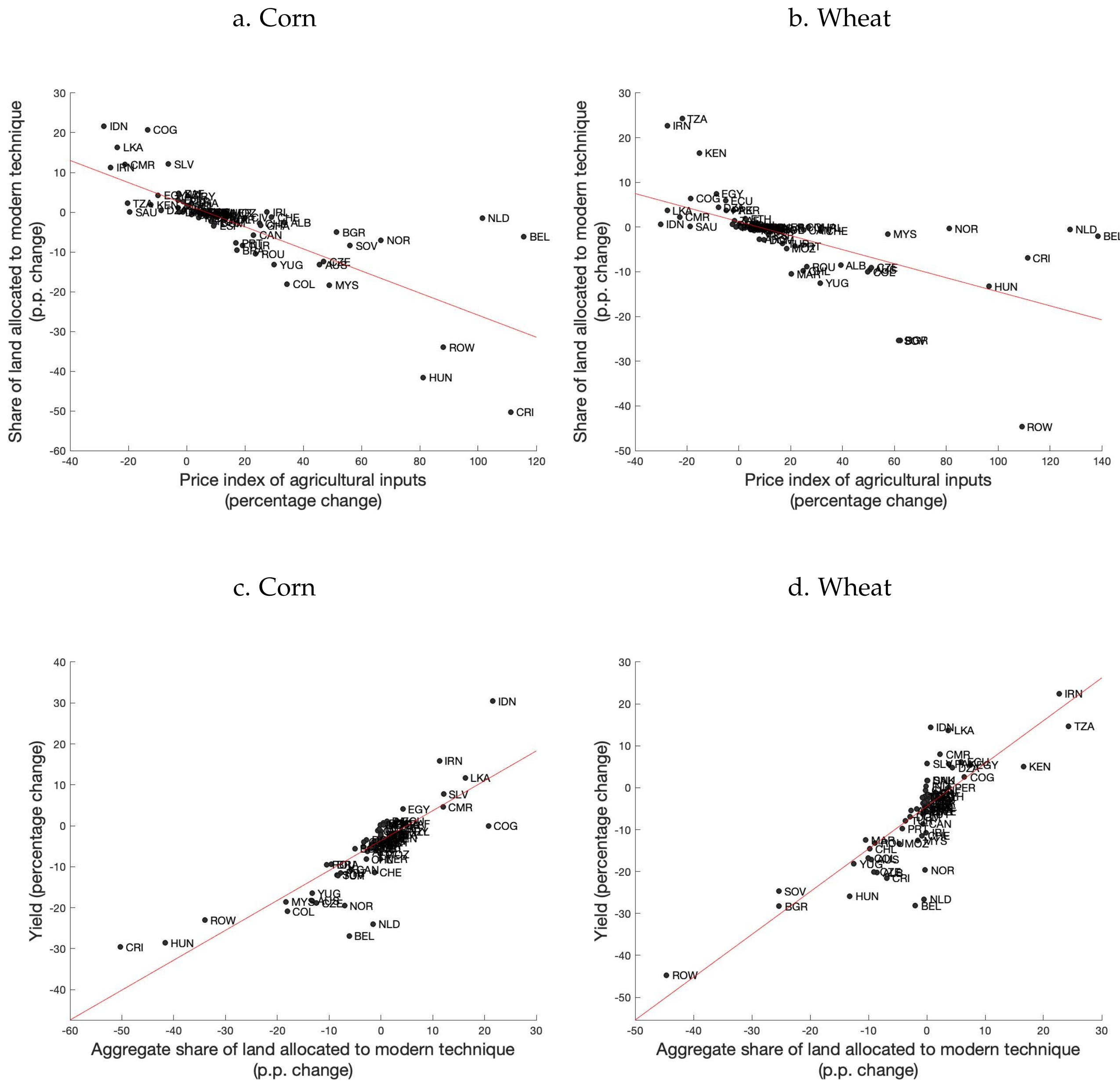
Globalization in agricultural inputs can create winners and losers because changes to trade costs are not uniform across countries. Consider Brazil and Iran. Between 1980 and 2010, due to the overall global fall of trade costs of agricultural inputs, the global demand rose for agricultural inputs. As a result, producer prices of fertilizers, pesticides, and farm machinery would rise in countries facing a sufficiently large global demand. Between 1980 and 2010, import costs reduced on average by around 50% for Brazil, whereas they fell only by an average of 10% for Iran. Putting these together, the consumer price of agricultural inputs in the counterfactual of 1980 compared to the baseline of 2010 would be on average 14% *higher* for Brazil, whereas it would be on average 38% *lower* for Iran. Consequently, in the counterfactual of 1980 compared to the baseline of 2010, the aggregate share of land allocated to modern technology would be 5.5 percentage point smaller for Brazil, and 22 percentage point larger for Iran. A takeaway from this example is that countries that fell behind in the process of globalization would end up facing higher prices of agricultural inputs that are largely set in the global market. Therefore, they would struggle to shift toward modern, input-intensive technologies, creating a barrier for their economic development.

We now turn our attention to how shifting from traditional technologies can bring about higher land productivities. In panels c and d of Figure (10), we show for selected crops the predicted change to yields against change to the share of land allocated to modern technologies. By and large across crops and countries, land productivities (yields) would be smaller in the counterfactual with trade costs of 1980 compared to the baseline of 2010. Across countries within a crop, yields are systematically lower, the smaller the land share of modern technology in the counterfactual outcome compared to the baseline. As reported in Table (A.4), at the global scale the counterfactual yields are 2 to 15 percent lower across crops. Hence, our results demonstrate notable global gains in agricultural land productivity as a result of globalization in agricultural inputs.

The benefits from modern technologies are reflected also in agricultural output per worker. We demonstrate this relationship in Figure (11) where we also show the importance of changes to agricultural input intensity in accounting for productivity gains. The smaller the share of modern technology in the counterfactual of 1980 compared to the baseline, the smaller the aggregate cost share of inputs and the smaller agricultural output per worker.

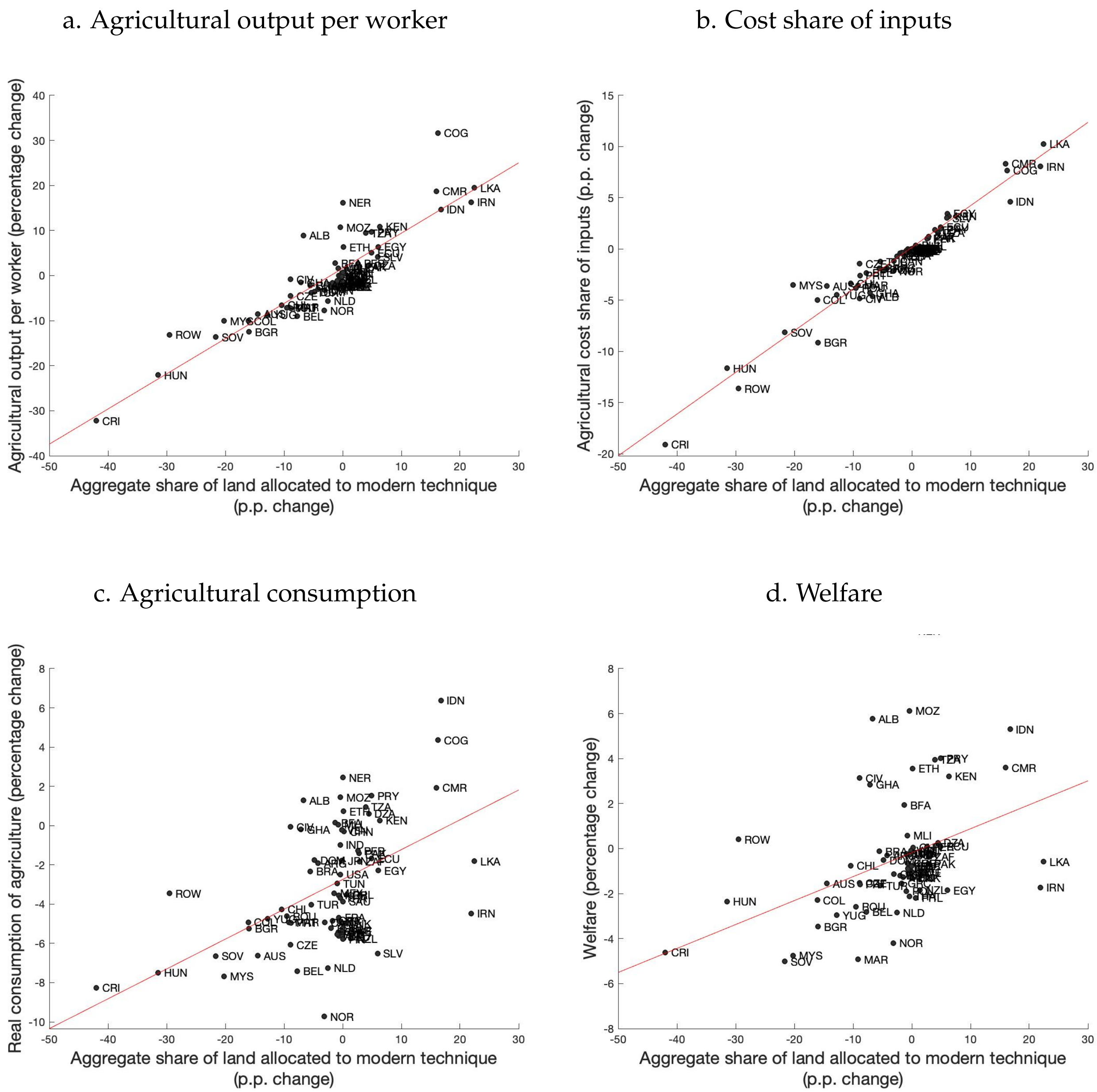
Lastly, we report the subsequent changes to agricultural prices and consumption as well as the overall welfare. In Figure (11) we show the scatter plot of percentage changes to real agricultural consumption (Panel c) and welfare (Panel d). In the counterfactual with trade costs of 1980 compared to the baseline of 2010, real consumption of agriculture tends to be systematically smaller across countries, the lower the land share of modern technology. Due to lower agricultural productivities in the counterfactual outcome, consumers in most countries would face higher price index of agricultural good. As a result of this price effect, consumers would shift their consumption away from food. However, since real income tends to be lower in the counterfactual outcome, the income effect would require a higher demand for food through non-homothetic preferences. Overall, these interactions would result in 2.41% reduction in the global food consumption and 0.74% reduction in the global welfare. That is, global welfare would reduce by 0.74% as a result of setting bilateral trade costs of agricultural inputs to their 1980 levels.

Figure 10: Effects of Globalization of Agricultural Inputs on Selected Crops



Notes: This figure shows how changes in key variables for selected crops if there had been no reductions in trade cost in agricultural inputs between 1980 and 2010.

Figure 11: Land share allocated to modern technique vs Selected measures of productivity and welfare



Notes: This figure shows the relationship between changes in agricultural consumption and the share of land allocated to modern technology, as well as the relationship between changes in welfare and the share of land allocated to modern technology in the absence of the reductions in trade cost in agricultural inputs between 1980 and 2010.

5.3 Additional Quantitative Exercises

[work in progress]

6 Conclusion

In this paper, we studied the consequences of globalization on agricultural productivity across the world geography. In doing so, we developed a general equilibrium framework that incorporates choices of crops and technologies in agricultural production. We connect our model to extremely rich data on agro-ecological suitability of fields for crops and technologies around the world. We find large productivity gains at the global scale, with notable distributional gains across countries due to international competition for input resources. In particular, countries that fell behind in the process of globalization would have lower adoption of input-intensive technologies.

New and richer high-resolution datasets are becoming available at the intersections of natural and social sciences. We take a step forward in incorporating these data into economic models. Integrating these datasets into economic models appear as a promising direction for future research, particularly with applications to resource and environment.

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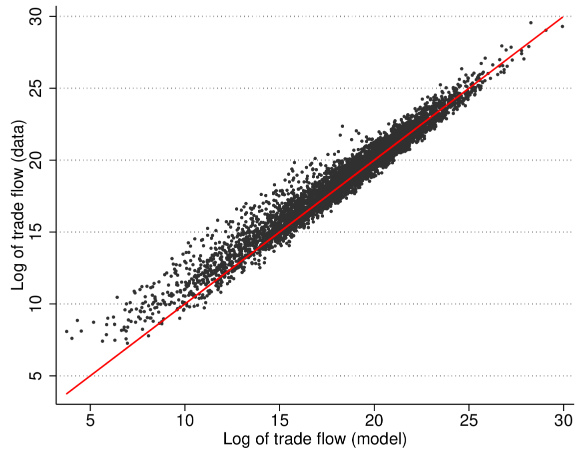
Appendix A Additional Figures and Tables

Table A.1: List of main variables and their data sources

Variable	**Source**
Country-level Data	
Employment in agriculture and nonagriculture	ILO
Value added in agriculture and nonagriculture	UN National Accounts
Agricultural land	FAO
Trade and production of crops	FAO
Producer price of crops	FAO
Trade and production of fertilizer, pesticide, farm machinery	UNIDO-IDSB, FAO, BACI
Trade and production of nonagriculture	BACI
Expenditure share on agriculture	World Bank-Global Consumption Database, WIOD
Gravity variables	CEPII
Population and GDP	ILO, Penn World Tables
Field-level Data	
Crop potential yield of low-input and high-input technologies	FAO-GAEZ
Crop actual yield	EarthStat
Crop land share	EarthStat
Total Land area	FAO, EarthStat

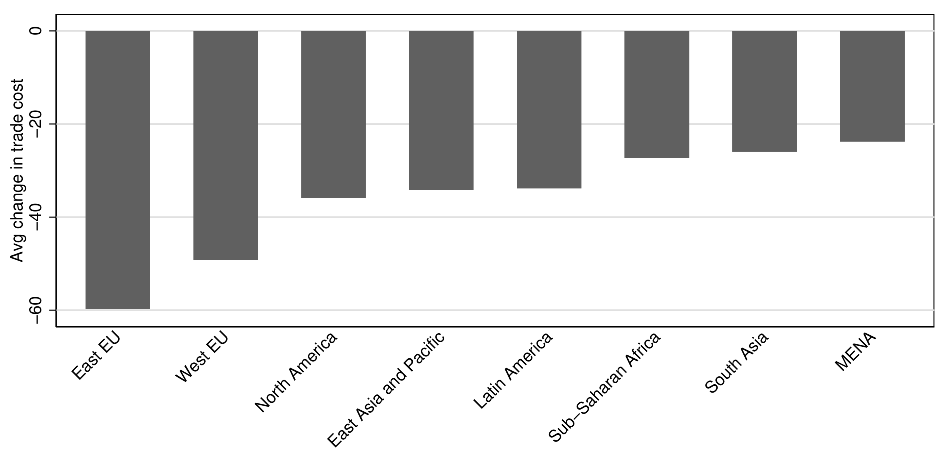
Notes. ILO: International Labor Organization, FAO: Food and Agriculture Organization, UNIDO: United Nations Industrial Development Organization, IDSB: Industrial Demand-Supply Balance Database at 4-digit ISIC, BACI: World trade database developed by the CEPII based on UN Comtrade, WIOD: World Input-Output Database, GAEZ: Global Agro-ecological zone

Figure A.1: Fit of the Model for Trade Flows in Non-Agricultural Input and Output



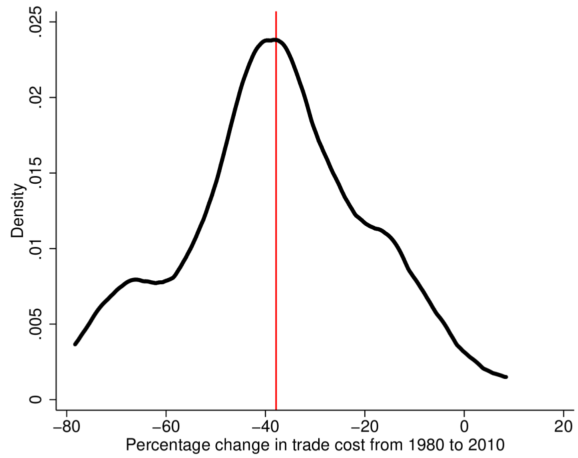
Notes: This figure shows the fit of the model in terms of trade flows for non-agricultural output and input. The red line shows the 45 degree line. Variables are represented in log 10 terms.

Figure A.2: Change in Trade Costs between 1980 and 2010 across regions.



Notes: This figure shows our estimates of the average of our estimates of changes in trade costs between 1980 and 2010 across countries within each region (weighted by trade flows).

Figure A.3: Change in Trade Costs between 1980 and 2010.



Notes: This figure shows the kernel density of our estimates of the changes in trade costs between 1980 and 2010 across countries. The red line denotes the average change in trade cost approximately at -37%.

Table A.2: Factor Shares in Agricultural Production Technology

	land (N)	labor (L)	material (M)
Traditional	0.578	0.422	0.000
Modern	0.381	0.206	0.413
Median across crops	0.222	0.250	0.528

Table A.3: Share of spending on domestic output

Quintile (1)	Ag output 2007 (2)	Man 2007 (3)	Ag input 2007 (4)	Ag output 1980 (5)	Man 1980 (6)	Ag input 1980 (7)	Ag output Δ (5)−(2)	Man Δ (6)−(3)	Ag input Δ (7)−(4)
1	0.950	0.612	0.393	0.970	0.803	0.409	0.019	0.190	0.016
2	0.918	0.652	0.541	0.925	0.808	0.509	0.007	0.156	-0.032
3	0.903	0.639	0.437	0.954	0.860	0.641	0.051	0.221	0.204
4	0.817	0.621	0.483	0.919	0.859	0.677	0.102	0.238	0.193
5	0.676	0.524	0.429	0.729	0.724	0.610	0.053	0.199	0.181
	0.807	0.610	0.405	0.756	0.778	0.365	-0.051	0.168	-0.040

Notes: Columns 7 and 9 show the change in the share of spending on domestic output.

Table A.4: Percentage change to crops yields across countries

banana	banana	cotton	corn	palm oil	potato	rice	soybean	sugarcane	tomato	wheat
Albania		-6.29%	-6.29%		-23.75%		-5.87%		-3.55%	-20.47%
Argentina	-3.94%	-4.71%	-3.49%		-5.75%	-4.88%	-6.54%	-3.91%	-2.28%	-5.32%
Australia	-20.46%	-17.85%	-18.98%	-22.67%	-18.68%	-21.64%	-23.59%	-10.50%	-24.27%	-17.16%
Austria			-5.62%		-5.83%		-6.07%		-5.06%	-6.19%
Belgium			-26.91%		-30.65%				-33.09%	-28.22%
Burkina Faso		-3.09%	-2.27%			-1.78%	-1.67%	-1.93%	-5.25%	
Bulgaria		-7.77%	-5.51%		-23.56%		-3.09%		-3.45%	-28.50%
Brazil	-9.27%	-8.80%	-9.18%	-8.87%	-6.23%	-9.29%	-6.19%	-3.81%	-7.97%	-5.42%
Canada			-10.63%		-8.96%		-18.97%		-4.23%	-8.58%
Switzerland			-11.31%		-12.29%		-3.89%		-10.27%	-11.48%
Chile			-8.14%		-16.14%		-7.23%		-12.69%	-14.65%
China	-0.30%	0.03%	-1.19%	-0.60%	-0.29%	-0.59%	0.67%	-0.34%	-0.25%	-0.58%
Cote dIvoire	-8.12%	-7.33%	-4.42%	-9.91%		-8.11%	-3.94%	-4.04%	-6.13%	
Cameroon	8.26%	5.44%	5.12%	8.91%	9.69%	0.21%	2.11%	-2.91%	4.09%	8.20%
Congo	-5.47%	-7.38%	0.18%	-3.66%	2.03%	-4.11%	-0.79%	-8.23%	-2.52%	2.67%
Colombia	-21.90%	-25.15%	-20.87%	-16.62%	-15.91%	-17.72%	-20.09%	-6.36%	-26.03%	-16.90%
Costa Rica	-34.31%	-20.00%	-29.49%	-29.94%	-24.15%	-34.31%	-23.72%	-7.15%	-32.13%	-21.75%
Czech Republic			-18.88%		-19.59%		-28.10%		-19.08%	-20.31%
Germany			-1.37%		-1.76%		-2.04%		-1.32%	-1.58%
Denmark					2.40%				1.81%	1.64%
Dominican Republic	-5.06%	-4.06%	-3.34%	-6.15%	-5.62%	-6.35%		-1.14%	-5.95%	-6.82%
Algeria		1.07%	0.79%		6.07%		0.52%	0.43%	0.78%	4.88%
Ecuador	1.22%	0.71%	1.43%	-0.23%	2.53%	1.28%	2.25%	-3.69%	0.87%	6.60%
Egypt		6.05%	4.67%		6.21%		2.86%		-1.05%	5.80%
Spain		-5.44%	-5.12%		-4.55%		-6.07%		-4.04%	-5.12%
Ethiopia	-3.32%	-3.88%	-4.01%		-3.42%	-3.34%	-3.46%	-4.32%	-7.24%	-2.06%
Finland					-4.23%					-3.71%
France		-4.09%	-4.84%		-4.67%	-4.90%	-6.60%		-4.47%	-4.65%
United Kingdom	-4.78%	-2.84%	-2.59%	-3.72%	-4.62%	-2.59%	-3.12%	-4.58%	-3.33%	-3.55%
Ghana	-5.57%	-3.55%	-3.98%	-9.68%		-4.42%	-6.82%	-3.08%	-10.16%	
Greece		-6.18%	-2.01%		-3.46%		-8.78%		-3.40%	-3.64%
Hungary			-28.25%		-27.96%		-25.48%		-16.29%	-26.03%
Indonesia	33.13%	25.51%	30.46%	22.06%	17.48%	22.24%	20.48%	6.95%	19.92%	14.67%
India	0.37%	0.10%	0.23%	0.30%	0.15%	0.21%	0.23%	-0.62%	0.32%	0.34%
Ireland					-11.61%					-10.69%
Iran		13.20%	16.93%		19.90%	45.29%	30.68%		2.92%	23.26%
Italy	-3.70%	-3.33%	-3.96%		-2.79%	-2.57%	-2.82%	-2.30%	-2.39%	-2.35%
Japan	-2.30%	-4.41%	-2.94%		-2.59%	-2.66%	-2.14%	-3.19%	-2.42%	-2.93%
Kenya	-1.42%	-1.52%	-2.87%		2.19%	-3.58%	-2.87%	-3.48%	-2.22%	5.13%
South Korea		-5.52%	-5.53%		-4.62%	-3.91%	-4.13%		-3.69%	-4.78%
Sri Lanka	16.63%	12.94%	11.73%	19.12%	16.18%	15.53%	26.75%	-0.80%	20.68%	13.86%
Morocco	-9.45%	-5.87%	-4.55%	-10.68%	-11.84%	-14.07%	-9.53%	-5.71%	-3.47%	-12.60%
Mexico	-4.36%	-4.76%	-3.83%	-5.00%	-3.19%	-4.17%	-3.78%	-5.26%	-4.02%	-3.01%
Mali		-3.02%	-0.76%			-0.93%	-0.64%	-0.70%	-1.88%	
Mozambique	-6.26%	-5.86%	-6.84%	-8.85%	-9.84%	-9.72%		-6.76%	-6.94%	-13.06%
Malaysia	-27.84%	-31.44%	-18.22%	-15.76%	-12.25%	-23.06%	-15.66%	-32.58%	-11.63%	-12.87%
Niger		-9.28%	-8.23%			-10.22%			-9.04%	
Netherlands	-28.98%	-36.11%	-23.84%	-27.98%	-27.65%	-26.89%	-42.07%	-44.08%	-28.10%	-26.55%
Norway	-20.99%	-22.21%	-19.40%	-21.42%	-19.71%	-18.61%	-25.09%	-27.01%	-23.08%	-19.67%
New Zealand	-4.14%	-4.92%	-1.07%		-5.50%	-4.88%	-6.45%	-5.06%	-4.46%	-4.17%
Pakistan	-1.18%	0.49%	1.15%		6.26%	3.92%	-2.53%	-1.77%	0.00%	5.83%
Peru	-1.13%	1.92%	0.30%	-1.06%	1.42%	0.03%	1.27%	-3.85%	1.51%	0.25%
Philippines	-1.05%	-1.15%	0.61%	-1.66%	-2.98%	-2.07%	-6.00%	-1.70%	-1.16%	-2.08%
Poland			-5.49%		-7.04%				-9.97%	-5.68%
Portugal		-13.38%	-11.40%		-10.97%		-17.03%		-7.82%	-9.73%
Paraguay	-0.22%	-0.22%	-1.28%	-1.51%	-0.16%	-1.53%	-0.13%	-4.38%	-0.41%	-1.64%
Romania		-9.73%	-9.28%		-14.05%		-5.33%		-5.06%	-13.09%
RoW	-34.27%	-20.27%	-23.43%	-29.66%	-42.17%	-31.99%	-28.02%	-16.53%	-35.08%	-44.63%
Saudi Arabia					-0.45%					2.06%
El Salvador	-0.78%	0.49%	7.41%		0.75%	3.29%	-1.51%	0.45%	1.19%	5.88%
fmr USSR	-25.15%	-16.54%	-12.04%	-23.59%	-26.20%	-27.57%	-7.44%	-14.95%	-15.64%	-24.68%
Sweden					-5.63%					-5.44%
Thailand	-1.99%	-3.78%	0.35%	-1.65%	-1.34%	0.18%	-4.71%	-1.24%	-0.63%	-2.08%
Tunisia		-1.32%	-2.13%		-2.18%		-2.27%		-1.83%	-2.34%
Turkey		-11.35%	-12.40%		-8.03%	-14.60%	-11.73%		-9.47%	-8.06%
Tanzania	-2.20%	0.03%	-2.04%	-4.23%	-7.29%	-6.43%	-2.28%	-4.32%	-2.19%	14.67%
United States	-2.97%	-3.16%	-3.51%		-3.53%	-3.58%	-2.44%	-4.63%	-2.98%	-3.45%
Venezuela	-0.43%	-1.02%	0.30%	-0.43%	-0.37%	-0.11%	-1.70%	-0.39%	-0.33%	-1.50%
fmr Yugoslavia		-14.01%	-16.51%		-16.80%	-8.65%	-19.86%		-15.02%	-18.39%
South Africa	-0.93%	-2.39%	0.66%		-0.60%	-0.18%	-1.91%	-3.29%	-0.54%	-0.92%
World	-2.92%	-6.28%	-5.39%	-8.33%	-14.58%	-2.70%	-3.80%	-8.86%	-7.85%	-10.25%

Table A.5: Percentage changes to agriculture-related variables and welfare

countries	share of land in modern tech	agriculture price	agriculture consumption	welfare
Albania	-6.80%	12.72%	1.37%	5.87%
Argentina	-4.27%	4.32%	-1.86%	-0.32%
Australia	-14.31%	13.42%	-6.64%	-1.55%
Austria	-0.70%	10.09%	-5.62%	-0.89%
Belgium	-8.18%	10.10%	-7.35%	-2.80%
Burkina Faso	-1.36%	4.28%	0.22%	1.99%
Bulgaria	-16.18%	10.21%	-5.28%	-3.50%
Brazil	-5.47%	6.97%	-2.27%	-0.14%
Canada	-3.15%	9.42%	-4.97%	-1.15%
Switzerland	-0.75%	10.08%	-5.36%	-0.64%
Chile	-10.52%	10.09%	-4.30%	-0.78%
China	0.21%	1.09%	-0.28%	0.05%
Cote dIvoire	-8.71%	7.59%	0.01%	3.11%
Cameroon	15.99%	2.86%	2.04%	3.69%
Congo	16.38%	8.87%	4.60%	10.86%
Colombia	-16.04%	10.31%	-4.91%	-2.33%
Costa Rica	-42.05%	13.52%	-8.15%	-4.60%
Czech Republic	-9.09%	11.65%	-6.08%	-1.54%
Germany	-0.01%	9.38%	-5.54%	-1.00%
Denmark	0.01%	7.64%	-4.95%	-1.29%
Dominican Republic	-4.94%	3.63%	-1.68%	-0.49%
Algeria	4.52%	-1.87%	0.60%	0.26%
Ecuador	4.94%	5.99%	-1.69%	0.07%
Egypt	6.21%	4.60%	-2.25%	-1.85%
Spain	-2.04%	9.52%	-5.19%	-1.19%
Ethiopia	0.10%	5.69%	0.81%	3.67%
Finland	0.03%	10.01%	-5.81%	-1.30%
France	-0.70%	8.78%	-4.65%	-0.89%
United Kingdom	-0.02%	10.05%	-5.34%	-0.76%
Ghana	-7.08%	6.72%	-0.14%	2.87%
Greece	-1.76%	9.66%	-4.82%	-1.54%
Hungary	-31.29%	13.76%	-7.45%	-2.33%
Indonesia	16.99%	-6.66%	6.36%	5.24%
India	-0.43%	2.95%	-0.96%	-0.22%
Ireland	-0.03%	9.96%	-5.26%	-0.78%
Iran	22.17%	9.87%	-4.46%	-1.72%
Italy	-0.68%	9.07%	-4.85%	-1.11%
Japan	-0.14%	4.33%	-1.76%	-0.22%
Kenya	6.30%	8.00%	0.40%	3.37%
South Korea	-0.69%	7.72%	-3.56%	-0.66%
Sri Lanka	22.04%	6.16%	-1.84%	-0.62%
Morocco	-9.24%	6.11%	-4.86%	-4.91%
Mexico	-1.54%	5.82%	-3.44%	-1.28%
Mali	-0.76%	2.16%	0.04%	0.53%
Mozambique	-0.44%	8.32%	1.58%	6.28%
Malaysia	-20.45%	10.32%	-7.63%	-4.73%
Niger	0.04%	11.54%	2.64%	9.93%
Netherlands	-2.66%	10.04%	-7.12%	-2.82%
Norway	-3.22%	14.23%	-9.63%	-4.18%
New Zealand	1.31%	10.72%	-5.73%	-1.84%
Pakistan	2.85%	3.99%	-1.31%	-0.60%
Peru	2.58%	4.49%	-1.30%	0.06%
Philippines	0.56%	8.63%	-3.36%	-2.08%
Poland	-0.98%	9.37%	-5.52%	-1.88%
Portugal	-8.96%	8.28%	-4.92%	-1.58%
Paraguay	4.89%	5.25%	1.53%	3.96%
Romania	-9.54%	10.20%	-4.62%	-2.59%
RoW	-29.87%	13.23%	-3.35%	0.51%
Saudi Arabia	0.05%	8.87%	-3.81%	-0.13%
El Salvador	5.52%	13.82%	-6.46%	-16.25%
fmr USSR	-22.17%	15.16%	-6.62%	-5.02%
Sweden	-0.04%	8.76%	-5.35%	-1.07%
Thailand	-0.47%	6.94%	-3.64%	-2.09%
Tunisia	-1.06%	7.02%	-2.85%	-0.22%
Turkey	-5.54%	7.90%	-3.95%	-1.61%
Tanzania	3.99%	5.90%	1.04%	4.09%
United States	-0.42%	5.50%	-2.48%	-0.29%
Venezuela	-0.12%	0.20%	-0.21%	-0.09%
fmr Yugoslavia	-12.87%	10.53%	-4.71%	-2.94%
South Africa	2.85%	3.30%	-1.78%	-0.37%
World	-9.22%	6.26%	-2.41%	-0.74%

Appendix B Data

Potential Yields. The data on potential yields (also called "maximum attainable yields") comes from Global Agro-Ecological Zones project, which is produced by the International Institute for Applied System Analysis (IIASA) and the Food and Organization of the United Nations (FAO). The goal of the project is to generate global datasets about agriculture at the disaggregated level of fields to facilitate the studies of the conditions affecting agricultural development and food security. The first version of the dataset was published in 2000 and since then there has been a continuous updating of the data.

FAO-GAEZ produces, among different sets of datasets, data about the agro-climatically attainable biomass and yield for specific land utilization types (LUTs) by crop, which we use in our analysis. 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 parameters of this function depends on each LUT and crop. Importantly, 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 should only capture differences in climatic conditions rather than levels of development of each country. 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.

The land utilization types in the data are divided into three groups. First, the low level of inputs, which corresponds to a farming system that is largely subsistence based. As described in the documentation. 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, which corresponds to a faming system that is partly market oriented. We do not use this dataset directly in our analysis since we our data does not allow us to identify an additional set of parameters associated with the factor intensity. Third, the high level of input use, which corresponds to a farming system that is mainly market oriented. In this case, production is fully mechanized and uses optimum applications of nutrients and chemical pest, disease and weed control.

Actual Yields and Agricultural Land. The data on actual yields come from Earthstat. Earthstat also provides geographic datasets at the disaggregated level of fields providing information about agriculture. 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 utilize information on actual yields by crop and on the share of land in agriculture. The data on actual yields use data from agricultural census and survey information on the areas from the smallest political units from each country. The level of disaggregation of the source data, however, varies substantially across countries. For example, in some countries, the data on actual yields is provided in terms of smaller areas that correspond to counties in the US, whereas in other countries data is provided at the state and province levels. Therefore, in our estimation we restricted our sample to the data constructed only from sources with sufficiently disaggregated information.

In addition to the yield level data, we also bring data from Earthstat on the share of a field dedicated to the production of crops. This dataset, different from the yields one, is constructed using a combination of agricultural datasets and satellite imagery. In our calibration, we therefore use the entire sample of cropland shares.

Trade and Gross Output for Agriculture and Non-Agricultural Goods (excluding agricultural inputs). The construction of our data for trade and gross output follows standard practices and datasets in the literature. We organized data from FAO-Stat on agricultural revenues in different crops for the year of 2010. We bring data on trade from Comtrade organized by Feenstra and from BACI. In addition, we bring data from United Nations on value added per broader sectors. Using these datasets, we compute gross output, export and imports for each country.

Trade and Gross Output for Agricultural Inputs. To construct our data on agricultural input sales and expenditures, we collected information on value added per sector from United Nations, on apparent absorption by industry from UNIDO and on exports and imports from Comtrade and BACI. Below, we explain how we combine these dataset to construct our final data on agricultural input sales and expenditures. We organized data for pesticide, machinery and fertilizer. The construction of our data for expenditure on fertilizers follows a slightly different approach since richer data on quantities is available from FAO. Our construction of the dataset is largely based on Comtrade, BACI, FAO and value added per sector data from United Nations. We use the UNIDO data, which is available for a limited set of years but contains complete information on apparent absorption by industry, to cross validate our construction of the dataset.

For pesticide and machinery, we first bring data on value exported and imported from the Comtrade organized by Feenstra and from BACI. This provides to us data on exports and imports. To generate data on gross production, we assume that the ratio of exports in agricultural machinery relative to manufacturing is equivalent to the ratio of gross output of agricultural machinery relative to manufacturing. The main assumption behind this approach is that both the manufacturing sector, and the subsector of agricultural machinery, are subject to similar trade and productivity shocks. To cross-validated our approach, we compared the apparent absorption in our data with the apparent absorption estimated by UNIDO, which contains information on apparent absorption for a limited number of years and countries. A regression of the log of absorption in our data against the log of absorption in UNIDO gives a coefficient of $\beta = 1.03$ with a R^2 of 0.78 ($N = 450$). In addition, a regression of the share of imports in total expenditure on agricultural machinery in our data against the share of imports in total expenditure in agricultural machinery in UNIDO data gives a coefficient of $\beta = 0.62$ with a R^2 of 0.45 ($N = 450$). We use a similar procedure to construct the data on gross output for pesticide. In this case, a regression of the log of absorption gives a coefficient of $\beta = 1.02$ with a R^2 of 0.73 ($N = 318$), and a regression of the share of imports in total expenditure a coefficient of $\beta = 0.55$ with a R^2 of 0.41 ($N = 318$).

For fertilizers, we proceed as follows. First, we bring data on quantity used, produced, imported and exported of fertilizer by country from FAO. FAO provides the data disaggregated by nutrients, i.e., nitrogren N, phosphate P and potassium K. To simplify our analysis we summed the weight of the total amount of nutrients coming from each type and looked at the aggregate use. We divide the value imported by total imports in quantity to obtain consumer prices. To obtain producer prices, we divide the sales of a country to itself in value and divide it by quantity. Again, we cross-validated our approach using data from UNIDO. We find that a regression of the log of gross output in our data against the log of gross output in UNIDO gives a coefficient of $\beta = 0.80$ with a R^2 of 0.83 ($N = 367$), and a regression of the share of fertilizer imports in our data agains the one in UNIDO gives a coefficient of $\beta = 0.45$ with a R^2 of 0.41 ($N = 367$).

Consumption Share of Agriculture. 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.

Appendix C Model

C.1 Costs and Output

Unit cost. Focusing on production in a plot given a choice of agriculture activity, we drop country-field-crop-technique 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

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

We write down the Lagrangian function and first order conditions,

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

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

$$\frac{rL}{mM} = \frac{\gamma^L}{\gamma^M} \Rightarrow L = \frac{\gamma^L}{\gamma^M}\frac{mM}{r}$$

$$\frac{wN}{mM} = \frac{\gamma^N}{\gamma^M} \Rightarrow N = \frac{\gamma^N}{\gamma^M}\frac{mM}{w}$$

Replace L and N into the production equation,

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

which then results:

$$M = (r/z)^{\gamma^L} w^{\gamma^N} m^{\gamma^M} \times \frac{\gamma^M}{m}$$
$$L = (r/z)^{\gamma^L} w^{\gamma^N} m^{\gamma^M} \times \frac{\gamma^L}{r}$$
$$N = (r/z)^{\gamma^L} w^{\gamma^N} m^{\gamma^M} \times \frac{\gamma^N}{w}$$

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, $L = 1$. 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

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

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

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

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,

$$\begin{aligned}
\mathbb{E}\left[a_{i,0}^f(\omega)\right] &= \mathbb{E}\left[a_{i,0}^f(\omega) \mid \omega \in \Omega_i^f\right] \Pr(\omega \in \Omega_i^f) + \mathbb{E}\left[a_{i,0}^f(\omega) \mid \omega \notin \Omega_i^f\right] \Pr(\omega \notin \Omega_i^f) \\
\mathbb{E}\left[a_{i,0}^f(\omega) \mid \omega \in \Omega_i^f\right] &= \frac{1}{\Pr(\omega \in \Omega_i^f)} \left[\mathbb{E}\left[a_{i,0}^f(\omega)\right] - \mathbb{E}\left[a_{i,0}^f(\omega) \mid \omega \notin \Omega_i^f\right] \Pr(\omega \notin \Omega_i^f)\right] \\
\mathbb{E}\left[a_{i,0}^f(\omega) \mid \omega \in \Omega_i^f\right] &= \frac{1}{\alpha_i^f}\left[a_{i,0}^f - a_{i,0}^f(1-\alpha_i^f)^{-1/\theta_1}(1-\alpha_i^f)\right] \\
\mathbb{E}\left[a_{i,0}^f(\omega) \mid \omega \in \Omega_i^f\right] &= \frac{a_{i,0}^f}{\alpha_i^f}\left[1-(1-\alpha_i^f)^{(\theta_1-1)/\theta_1}\right] \qquad \text{(A.1)}
\end{aligned}$$

The field-level quantity required for fixed investments in agriculture, S_i^f, equals the average fixed cost requirement conditional on plots being used for agriculture times the number of plots used for agriculture,

$$S_i^f = \mathbb{E}\left[a_{i,0}^f(\omega) \mid \omega \in \Omega_i^f\right] \alpha_i^f L_i^f$$

Using equation (A.1),

$$S_i^f = a_{i,0}^f L_i^f \left[1 - (1 - \alpha_i^f)^{(\theta_1 - 1)/\theta_1} \right] \tag{A.2}$$

C.3 McFadden's Theorem

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

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

where Ω is the set of alternatives, q_i is the non-stochastic component of the objective function, and u_i is the stochastic term. For example, 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 nonnegative, 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,

- The following function

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

is a multivariate extreme value distribution.

- Choice probabilities satisfy

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

C.4 Discrete Choice, Generalized Extreme Value, and Choice Probabilities

One Nest. Suppose H is given by

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

With $\rho = \frac{1}{1-\sigma}$, as long as $0 \leq \sigma < 1$, the conditions in the theorem are satisfied. Then,

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

gives a multivariate EV distribution. σ is the correlation between $(u_j, u_{j'})$. Choice probabilities satisfy

$$\begin{aligned}
\pi_i &= -\frac{\partial}{\partial q_i} \ln \Big(e^{-\rho q_1} + ... + e^{-\rho q_K}\Big)^{1/\rho} \\
&= \frac{e^{-\rho q_i}\Big(e^{-\rho q_1} + ... + e^{-\rho q_K}\Big)^{1/\rho - 1}}{\Big(e^{-\rho q_1} + ... + e^{-\rho q_K}\Big)^{1/\rho}} \\
&= \frac{e^{-\rho q_i}}{e^{-\rho q_1} + ... + e^{-\rho q_K}}
\end{aligned}$$

From Type I EV to Type II EV. Recall the discrete choice problem,

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

This maximization is equivalent to

$$\max_{i\in\Omega} w_i z_i$$

where $q_i = -\theta \ln w_i a_i$, and $u_i = \theta \ln(z_i/a_i)$. Then, by a change of variable, probability distribution of $\mathbf{z}(\omega) = (z_1(\omega), ..., z_K(\omega))$ is given by

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

which is a Fréchet (Type II EV) distribution. Replacing for $q_i = -\theta \ln w_i a_i$, choice probabilities are

$$\pi_i = \frac{(w_i a_i)^{\theta\rho}}{\sum_{k=1}^{K} (w_k a_k)^{\theta\rho}}$$

EK, Independent Draws. Let $\rho = 1$ (or equivalently, $\sigma = 0$) meaning that $z_1(\omega)$, ..., $z_K(\omega)$ are independent. The probability distribution simplifies to

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

Thanks to independence, distribution of $z_k(\omega)$ equals

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

which is used in EK. Choice probabilities are

$$\pi_i = \frac{(w_i/a_i)^{\theta}}{\sum_{k=1}^{K} (w_i a_i)^{\theta}}$$

Two Nests. Suppose H is given by

$$H(\mathbf{y}) = \sum_{k \in K} a_k \Big[\sum_{i \in \Omega_k} y_{ik}^{\theta_k} \Big]^{1/\theta_k}$$

Then,

$$F(\mathbf{u}) = \exp\left[- \sum_{k \in K} a_k \Big[\sum_{i \in \Omega_k} e^{-\theta_k u_{ik}} \Big]^{1/\theta_k} \right]$$

is a multivariate EV distribution, satisfying these familiar choice probabilities

$$\begin{aligned}\pi_{ik} &= -\frac{\partial}{\partial q_{ik}} \ln \left[\sum_{k \in K} a_k \Big[\sum_{i \in \Omega_k} e^{-\theta_k q_{ik}} \Big]^{1/\theta_k} \right] \\ &= \frac{e^{-\theta_k q_{ik}} a_k \Big[\sum_{i \in \Omega_k} e^{-\theta_k q_{ik}} \Big]^{1/\theta_k - 1}}{\sum_{k \in K} a_k \Big[\sum_{i \in \Omega_k} e^{-\theta_k q_{ik}} \Big]^{1/\theta_k}} \\ &= \frac{e^{-\theta_k q_{ik}}}{\sum_{i \in \Omega_k} e^{-\theta_k q_{ik}}} \times \frac{a_k \Big[\sum_{i \in \Omega_k} e^{-\theta_k q_{ik}} \Big]^{1/\theta_k}}{\sum_{k \in K} a_k \Big[\sum_{i \in \Omega_k} e^{-\theta_k q_{ik}} \Big]^{1/\theta_k}}\end{aligned}$$

If by our specification, within nest k let $q_{ik} = -\phi_k \ln x_{ik}$, and define $\nu_k = \phi_k \theta_k$, then

$$\begin{aligned}\pi_{ik} &= \frac{x_{ik}^{\phi_k \theta_k}}{\sum_{i \in \Omega_k} x_{ik}^{\phi_k \theta_k}} \times \frac{a_k \Big[\sum_{i \in \Omega_k} x_{ik}^{\phi_k \theta_k} \Big]^{1/\theta_k}}{\sum_{k \in K} a_k \Big[\sum_{i \in \Omega_k} x_{ik}^{\phi_k \theta_k} \Big]^{1/\theta_k}} \\ &= \frac{x_{ik}^{\nu_k}}{\sum_{i \in \Omega_k} x_{ik}^{\nu_k}} \times \frac{a_k \Big[\sum_{i \in \Omega_k} x_{ik}^{\nu_k} \Big]^{\phi_k/\nu_k}}{\sum_{k \in K} a_k \Big[\sum_{i \in \Omega_k} x_{ik}^{\nu_k} \Big]^{\phi_k/\nu_k}}\end{aligned}$$

C.5 Expected Value conditional on selection

One Nest. In the simple case with one nest, we allow for a positive correlation σ, with $\rho \equiv \frac{1}{1-\sigma}$, and $u_i = \theta \ln(z_i/a_i)$, then

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

Discrete choice problem, with $q_i = -\theta \ln w_i/a_i$, is $\max_i -q_i + u_i$, or equivalently,

$$\max_i w_i z_i$$

The choice probability is given by

$$\pi_i = \frac{(w_i a_i)^{\theta\rho}}{\sum_{k=1}^{K} (w_k a_k)^{\theta\rho}}$$

Let $\Omega_j = \{\omega : w_j z_j = \max_i w_i z_i\}$. Define

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

which equals

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

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

$$\begin{aligned}
\widetilde{F}_1(z) &\equiv \Pr\Big(z_1(\omega) \le z \mid \omega \in \Omega_1\Big) \\
&= \frac{1}{\Pr(\omega \in \Omega_1)} \Pr\Big(z_1(\omega) \le z,\ w_1 z_1(\omega) \ge w_j z_j(\omega)\Big) \\
&= \frac{1}{\pi_1} \Pr\Big(z_1(\omega) \le z,\ z_j(\omega) \le \frac{w_1}{w_j} z_1(\omega)\Big) \\
&= \frac{1}{\pi_1} \int_{z_1=0}^{z} \int_{z_2=0}^{\frac{w_1}{w_2}z} \int_{z_K=0}^{\frac{w_1}{w_K}z} f(z_1, z_2, ..., z_K) dz_K ... dz_2 dz_1 \\
&= \frac{1}{\pi_1} \int_{z_1=0}^{z} F^1(z, \frac{w_1}{w_2} z, ..., \frac{w_1}{w_K} z) dz_1 \\
&= \frac{1}{\pi_1} \int_{z_1=0}^{z} \theta a_1^{\theta\rho} z^{-\theta\rho-1} \Big((\frac{z}{a_1})^{-\theta\rho} + \sum_{k=2}^{K} (\frac{w_1 z}{w_k a_k})^{-\theta\rho} \Big)^{\frac{1}{\rho}-1} \exp\left[-\Big((\frac{z}{a_1})^{-\theta\rho} + \sum_{k=2}^{K} (\frac{w_1 z}{w_k a_k})^{-\theta\rho} \Big)^{\frac{1}{\rho}} \right] dz_1 \\
&= \frac{1}{\pi_1} \int_{z_1=0}^{z} \theta a_1^{\theta} z^{-\theta-1} \Big(1 + \sum_{k=2}^{K} (\frac{w_1 a_1}{w_k a_k})^{-\theta\rho} \Big)^{\frac{1}{\rho}-1} \exp\left[-z^{-\theta} a_1^{\theta} \Big(1 + \sum_{k=2}^{K} (\frac{w_1 a_1}{w_k a_k})^{-\theta\rho} \Big)^{\frac{1}{\rho}} \right] dz_1 \\
&= \frac{1}{\pi_1} \int_{z_1=0}^{z} \theta a_1^{\theta} z^{-\theta-1} \Big((w_1 a_1)^{-\theta\rho} \sum_{k=1}^{K} (w_k a_k)^{\theta\rho} \Big)^{\frac{1}{\rho}-1} \exp\left[-z^{-\theta} a_1^{\theta} \Big((w_1 a_1)^{-\theta\rho} \sum_{k=1}^{K} (w_k a_k)^{\theta\rho} \Big)^{\frac{1}{\rho}} \right] dz_1 \\
&= \int_{z_1=0}^{z} \theta a_1^{\theta} z^{-\theta-1} \Big(\frac{1}{\pi_1} \Big)^{\frac{1}{\rho}} \exp\left[-z^{-\theta} a_1^{\theta} \Big(\frac{1}{\pi_1} \Big)^{\frac{1}{\rho}} \right] dz_1
\end{aligned}$$

which is a Fréchet distribution with location parameter $a_1^{\theta} \pi_1^{-1/\rho}$ and dispersion parameter θ. It is straightforward to show that the expected value of a Fréchet distribution with location T and dispersion θ equals $\Gamma(1-1/\theta)T^{1/\theta}$. So, the expected value of $z_1(\omega)$ conditional on $\omega \in \Omega_1$ equals

$$\Gamma(1-1/\theta) a_1 \pi_1^{-1/\theta\rho}$$

To make a closer connection to our notation, let $\theta_2 \equiv \theta\rho$, and $\theta_1 \equiv \theta$

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

Then the conditional expected value is given by

$$\Gamma(1 - 1/\theta_1) a_1 \pi_1^{-1/\theta_2}$$

Two Nests. For notational simplicity let us have a two-branch tree in the upper nest and K-branch sub-trees in the lower nests. Probability distribution is:

$$F(z_{11}, ..., z_{1K}, z_{21}, ..., z_{2K}) = \exp\left[-\left\{ \Big(\sum_{k=1}^{K} (z_{1k}/a_{1k})^{-\theta\rho} \Big)^{\frac{1}{\rho}} + \Big(\sum_{k=1}^{K} (z_{2k}/a_{2k})^{-\theta\rho} \Big)^{\frac{1}{\rho}} \right\} \right]$$

Choice probabilities are:

$$\pi_{11} = \frac{(w_1 a_1)^{\theta\rho}}{H_1^{\theta\rho}} \frac{H_1^{\theta}}{H_1^{\theta} + H_2^{\theta}}, \quad H_s^{\theta\rho} = (w_{s1} a_{s1})^{\theta\rho} + ... + (w_{sK} a_{sK})^{\theta\rho}$$

Note that

$$H_1^{\theta} = \Big[\sum_k (w_{1k} a_{1k})^{\theta\rho} \Big]^{1/\rho}, \quad H_2^{\theta} = \Big[\sum_k (w_{2k} a_{2k})^{\theta\rho} \Big]^{1/\rho}$$

Let $F^{11}(z_{11}, ..., z_{1K}, z_{21}, ..., z_{2K}) \equiv \frac{\partial}{\partial z_{11}} F(z_{11}, ..., z_{1K}, z_{21}, ..., z_{2K})$,

$$\begin{aligned} F^{11} &= \theta a_{11}^{\theta\rho} z_{11}^{-\theta\rho - 1} \Big(\sum_{k=1}^{K} (z_{1k}/a_{1k})^{-\theta\rho} \Big)^{\frac{1}{\rho} - 1} \\ &\quad \times \exp\left[-\left\{ \Big(\sum_{k=1}^{K} (z_{1k}/a_{1k})^{-\theta\rho} \Big)^{\frac{1}{\rho}} + \Big(\sum_{k=1}^{K} (z_{2k}/a_{2k})^{-\theta\rho} \Big)^{\frac{1}{\rho}} \right\} \right] \end{aligned}$$

Probability distribution of $z_{11}(\omega)$ conditional on $\omega \in \Omega_{11}$,

$$\begin{aligned}
\widetilde{F}_{11}(z) &\equiv \Pr\Big(z_{11}(\omega) \leq z \mid \omega \in \Omega_{11}\Big) \\
&= \frac{1}{\Pr(\omega \in \Omega_{11})} \Pr\Big(z_{11}(\omega) \leq z,\ w_{sk} z_{sk}(\omega) \leq w_{11} z_{11}(\omega)\Big) \\
&= \frac{1}{\pi_{11}} \Pr\Big(z_{11}(\omega) \leq z,\ z_{sk}(\omega) \leq \frac{w_{11}}{w_{sk}} z_{11}(\omega)\Big) \\
&= \frac{1}{\pi_{11}} \int_{z_{11}=0}^{z} F^{11}(z, \frac{w_{11}}{w_{12}}z, ..., \frac{w_{11}}{w_{1K}}z, \frac{w_{11}}{w_{21}}z, \frac{w_{11}}{w_{22}}z, ..., \frac{w_{11}}{w_{2K}}z) dz_{11} \\
&= \frac{1}{\pi_{11}} \int_{z_{11}=0}^{z} \theta a_{11}^{\theta\rho} z^{-\theta\rho-1} \Big((z/a_{11})^{-\theta\rho} + \sum_{k=2}^{K} (\frac{w_{11}z}{w_{1k}a_{1k}})^{-\theta\rho}\Big)^{\frac{1}{\rho}-1} \\
&\qquad \times \exp\Bigg[- \Bigg\{ \Big((z/a_{11})^{-\theta\rho} + \sum_{k=2}^{K} (\frac{w_{11}z}{w_{1k}a_{1k}})^{-\theta\rho}\Big)^{\frac{1}{\rho}} + \Big(\sum_{k=1}^{K} (\frac{w_{11}z}{w_{2k}a_{2k}})^{-\theta\rho}\Big)^{\frac{1}{\rho}} \Bigg\} \Bigg] dz_{11} \\
&= \frac{1}{\pi_{11}} \int_{z_{11}=0}^{z} \theta a_{11}^{\theta} z^{-\theta-1} \Big(1 + \sum_{k=2}^{K} (\frac{w_{11}a_{11}}{w_{1k}a_{1k}})^{-\theta\rho}\Big)^{\frac{1}{\rho}-1} \\
&\qquad \times \exp\Bigg[- \Bigg\{ z^{-\theta} a_{11}^{\theta} \Big(1 + \sum_{k=2}^{K} (\frac{w_{11}a_{11}}{w_{1k}a_{1k}})^{-\theta\rho}\Big)^{\frac{1}{\rho}} + z^{-\theta} a_{11}^{\theta} \Big(\sum_{k=1}^{K} (\frac{w_{11}a_{11}}{w_{2k}a_{2k}})^{-\theta\rho}\Big)^{\frac{1}{\rho}} \Bigg\} \Bigg] dz_{11} \\
&= \frac{1}{\pi_{11}} \int_{z_{11}=0}^{z} \theta a_{11}^{\theta} z^{-\theta-1} \Big((w_{11}a_{11})^{-\theta\rho} \Big[\sum_{k=1}^{K} (w_{1k}a_{1k})^{\theta\rho}\Big]\Big)^{\frac{1}{\rho}-1} \\
&\qquad \times \exp\Bigg[- z^{-\theta} a_{11}^{\theta} \Bigg\{ \Big((w_{11}a_{11})^{-\theta\rho} \sum_{k=1}^{K} (w_{1k}a_{1k})^{\theta\rho}\Big)^{\frac{1}{\rho}} + \Big((w_{11}a_{11})^{-\theta\rho} \sum_{k=1}^{K} (w_{2k}a_{2k})^{\theta\rho}\Big)^{\frac{1}{\rho}} \Bigg\} \Bigg] dz_{11} \\
&= \int_{z_{11}=0}^{z} \theta a_{11}^{\theta} z^{-\theta-1} \Big((w_{11}a_{11})^{-\theta} (H_1^{\theta} + H_2^{\theta})\Big) \\
&\qquad \times \exp\Bigg[- z^{-\theta} a_{11}^{\theta} \Big((w_{11}a_{11})^{-\theta} (H_1^{\theta} + H_2^{\theta})\Big) \Bigg] dz_{11}
\end{aligned}$$

This is a Fréchet distribution with location parameter $a_{11}^{\theta}\Big((w_{11}a_{11})^{-\theta}(H_1^{\theta} + H_2^{\theta})\Big)$ and dispersion parameter θ. Note that probability of choosing (s, k) equals probability of choosing k conditional on s times the probability of choosing s,

$$\pi_{sk} = \alpha_{k|s} \alpha_s$$

The "inverse of location parameter" is

$$a_{11}^{-\theta} \frac{(w_{11}a_{11})^{\theta}}{H_1^{\theta} + H_2^{\theta}} = a_{11}^{-\theta} \Big(\frac{(w_{11}a_{11})^{\theta\rho}}{H_1^{\theta\rho}}\Big)^{1/\rho} \frac{H_1^{\theta}}{H_1^{\theta} + H_2^{\theta}} = a_{11}^{-\theta} \alpha_{1|1}^{1/\rho} \alpha_1$$

As before, let $\theta_2 = \theta\rho$ and $\theta_1 = \theta$, then the inverse of location parameter is

$$a_{11}^{-\theta_1} \alpha_{k|s}^{\theta_1/\theta_2} \alpha_s$$

Expected value of a Fréchet distributed random variable with location T and dispersion θ equals $\bar{\gamma} T^{1/\theta}$ with $\bar{\gamma} \equiv \Gamma(1 - 1/\theta)$. Thus, here the expected value conditional on selection equals

$$\bar{\gamma} \Big[a_{11}^{-\theta_1} \alpha_{k|s}^{\theta_1/\theta_2} \alpha_s \Big]^{-1/\theta_1} = \bar{\gamma} \Big(a_{sk} \Big) \Big(\alpha_{k|s} \Big)^{-1/\theta_2} \Big(\alpha_s \Big)^{-1/\theta_1}$$

C.6 Derivations for recasting the micro to macro problem

In this section, we recast the land use problem onto crop supply. We show (i) that the following problem reproduces equation (22), and (ii) the Lagrange multipliers reproduce returns to land. Using $Q^f_{i,k\tau} = (1/\gamma^L_{k\tau}) \widetilde{h}_{i,k\tau} \widetilde{L}^f_{i,k\tau}$, the problem of the landowner in Section 3.5 can be written as:

$$\begin{aligned}
\max_{\{Q^f_{i,k\tau}\}_{k,\tau},\, \{\widetilde{Q}^f_{i,k}\}_k} \quad & \sum_{\tau \in \mathcal{T}} \sum_{k \in \mathcal{K}} \gamma^L_{k\tau} p_{i,k} Q^f_{i,k\tau} \\
\text{subject to} \quad & \Bigg[\sum_{\tau \in \mathcal{T}} \Big(\frac{Q^f_{i,k\tau}}{v^f_{i,k\tau}} \Big)^{\frac{\theta_2}{\theta_2 - 1}} \Bigg]^{\frac{\theta_2 - 1}{\theta_2}} \leq \widetilde{Q}^f_{i,k} \\
& \Bigg[\sum_{k \in \mathcal{K}} (\widetilde{Q}^f_{i,k})^{\frac{\theta_1}{\theta_1 - 1}} \Bigg]^{\frac{\theta_1 - 1}{\theta_1}} \leq L^f_i
\end{aligned}$$

where

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

The Lagrangian function is:

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

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

$$\begin{aligned} \gamma^L_{k\tau} p_{i,k} &= \lambda^f_{i,k} (v^f_{i,k\tau})^{-\frac{\theta_2}{\theta_2 - 1}} (Q^f_{i,k\tau})^{\frac{1}{\theta_2 - 1}} (\widetilde{Q}^f_{i,k})^{-\frac{1}{\theta_2 - 1}} && \text{(A.3)} \\ \lambda^f_{i,k} &= \mu^f_i (\widetilde{Q}^f_{i,k})^{\frac{1}{\theta_1 - 1}} (L^f_i)^{-\frac{1}{\theta_1 - 1}} && \text{(A.4)} \end{aligned}$$

Using equation (A.3), and $v^f_{i,k\tau} = \widetilde{h}_{i,k\tau} a^f_{i,k\tau} (\gamma^L_{k\tau})^{-1}$,

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

or, equivalently,

$$\frac{Q^f_{i,k\tau}}{v^f_{i,k\tau}} = (\lambda^f_{i,k})^{-(\theta_2 - 1)} (p_{i,k})^{\theta_2 - 1} (a^f_{i,k\tau} \widetilde{h}_{i,k\tau})^{\theta_2 - 1} \widetilde{Q}^f_{i,k} \tag{A.5}$$

Recall the definition of $H^f_{i,k}$ from equation (19),

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

Using equation (A.5),

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

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

$$\lambda^f_{i,k} = H^f_{i,k} \tag{A.6}$$

Using equation (A.4),

$$\widetilde{Q}^f_{i,k} = (\lambda^f_{i,k})^{\theta_1 - 1} (\mu^f_i)^{-(\theta_1 - 1)} L^f_i \tag{A.7}$$

which we use to derive the following relationship:

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

Replacing $\lambda^f_{i,k} = H^f_{i,k}$ we find the shadow price of cropland, μ^f_i,

$$\mu^f_i = \Big[\sum_k (H^f_{i,k})^{\theta_1}\Big]^{\frac{1}{\theta_1}} \tag{A.8}$$

Plug μ^f_i from (A.8) into (A.7),

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

Putting things together,

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

which is the same as equation (22).