Skill Investment, Farm Size Distribution and Agricultural Productivity

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Abstract

This paper addresses the question why agricultural productivity is so low in poor countries. World Census of Agriculture reveals that agricultural production is of much smaller scale in developing countries. I construct a two-sector OLG model where agricultural production is carried out by heterogeneous farmers. At the farm level, optimal scale and productivity is tied to the farmer's idiosyncratic skill, which can grow over time as a result of optimal investment. At the aggregate, self-selection determines the average skill of farmers and hence the measured agricultural productivity. The calibrated model can explain almost all of the differences in agricultural productivity between the 80th and 20th percentile countries in the sample. Endogenously generated farm size distributions are close to the actual ones as well.

JEL Classification: O11, O13, O41

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1 Introduction

The agricultural sector in poor countries appears disproportionately unproductive, yet employs most of the labor force[1]. Low living standards are driven by both high labor share and

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[1]See also Gollin *et al.* (2004, 2007), Caselli (2005), Restuccia *et al.* (2008)

low labor productivity in the traditional sector. A counterfactual calculation will illustrate this point succinctly. If all countries would have the U.S. agricultural productivity, and maintain their own labor allocation and nonagricultural productivity, cross-country income differences would almost disappear[2]. Hence the key question is why productivity is so low in the agricultural sector of poor countries.

This paper addresses the question by focusing on the scale of production in the farming sector, which exhibits vast variation across countries, as I will document later. Farming in poor countries are shown to be of much smaller scale compared to rich countries. I incorporate this feature into a model, in which optimal scale is determined by the farmer's idiosyncratic skill at the farm level. In poor countries, the average farmer possesses low skill as a result of self-selection and suboptimal investment in skill growth. As a result, the agricultural sector operates in small scale and has low measured labor productivity.

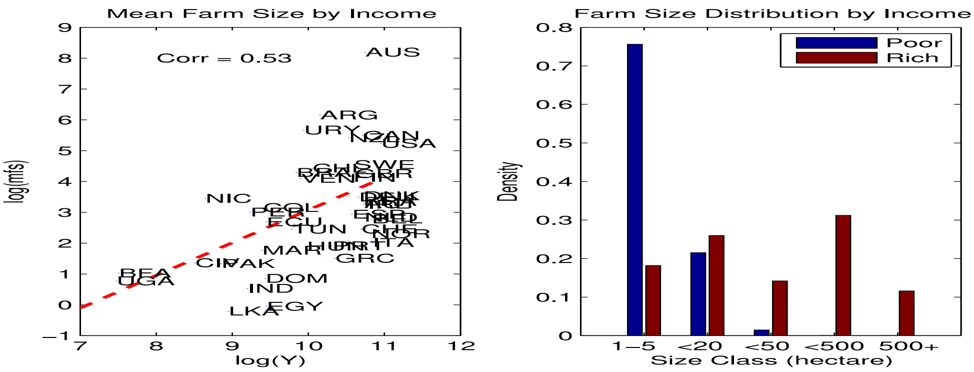
I take advantage of the recently available World Census of Agriculture (WCA) published by the Food and Agriculture Organization (FAO) of the United Nations. FAO compiles national agriculture censuses and presents summary statistics in a common format. The data are internationally comparable and cover a large set of countries in different phases of development. From the data, I construct the distribution of farms in different size categories for a sample of 40 countries. The main findings are: (1) Mean holding size[3] positively and strongly correlates with income level. Figure 1 (left panel) plots mean farm size (log) against income per worker (log) in 1996. Mean farm size ranges from below 1 hectare in the poorest countries to above 1000 hectares in the richest countries; (2) Agricultural production in low income countries concentrates disproportionately on very small farms. Figure 1 (right panel) plots the (average) farm size distributions of two sets of countries (rich and poor)[4]. In Uganda, for example, 73% of the farms operate with less than 5 hectares of land. In contrast, 50% of the farms in the U.S. exceed 50 hectares in size.

Using data from U.S. census of agriculture, I find larger farmers to be markedly more productive, relative to the smaller ones. In terms of output per worker, it is not uncommon to observe a 16-fold gap between a 2000+-acre farm and a 50-acre farm in 2007, as illustrated

[2]Even if all countries have the U.S. *relative* productivity (agriculture/nonagriculture) and maintain their own labor allocation and nonagricultural productivity, would shrink income differences to a factor of 6, from a factor of 32, between the 90th and 10th percentile countries.

[3] In WCA, a holding is defined as "an economic unit of agricultural production under single management comprising all livestock kept and all land used wholly or partly for agricultural production purposes, without regard to title, legal form, or size"

[4]Rich countries: U.S, Canada, Australia, Norway, Switzerland. Poor countries: Uganda, Burkina Faso, Ivory Coast, Pakistan, Sri Lanka.



Source: GDP per worker: PWT 6.1; Mean farm size: WCA, 1990, 2000.

Figure 1: Scale of Production in Agriculture Across Income Levels

in Figure 2. In value added terms, the productivity differences are even more pronounced - by a factor of 30 between the maximum and minimum scale[5]. These productivity differences appear robust in earlier censuses (92, 97 and 02) as well. While WCA does not report farm productivity by size category, international evidences are available from studies of individual countries[6]. These studies all point to a positive correlation between farm size and *labor* productivity[7]. Given increasing labor productivity with size, differences in the composition of farms clearly map into differences in measured labor productivity in the agricultural sector. Quantitatively, I show that differences in the composition of farms can account for around 1/3 of the observed variation in agricultural productivity for a sample of 40 countries (Appendix B.2).

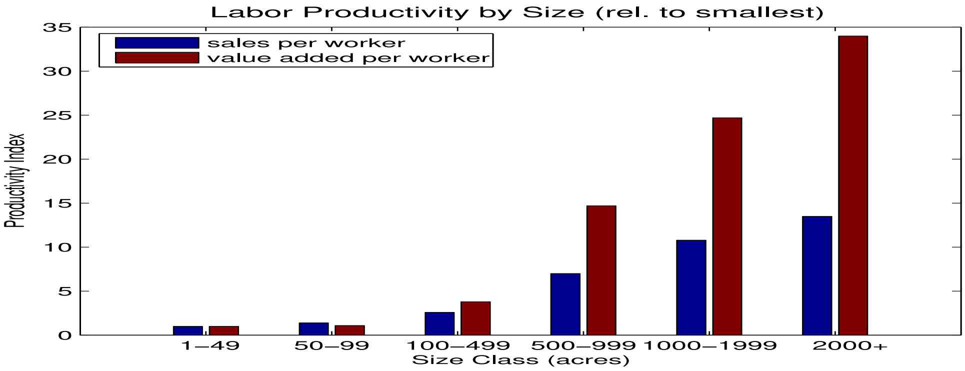
In essence agricultural productivity is viewed to be determined by two things: how productive the economy is overall and how productive the individuals self-selecting into the agricultural sector are. In this paper, the former is exogenous and inferred from data. The latter, however, is determined endogenously through two channels: occupation choice and skill investment. In the model, individuals are heterogeneous in their "farming skill", which is intended to capture their idiosyncratic productivity in the agricultural sector[8]. Farmers act as price takers and retain residual profit. Outside the agricultural sector, wage work is

[5]Substantial differences remain when productivity is measured residually. Computed Solow residual ranges from 3 to 5 times higher in the largest farms, relative to the smallest ones.

[6]See Fan & Chan-Kang (2005) for a set of asian countries; Byiringiroa & Reardon (1996) for Rwanda

[7]There is a large literature debating the relation between farm size and *land* productivity. See Feder (1985) and reference therein

[8]Assuncao & Ghatakb (2003) also introduce a notion of farming skill, and analyze how this unobserved characteristic of farmers affects the *measured* correlation between farm size and *land* productivity in a partial equilibrium.



Source: 2007 U.S. Census of Agriculture, Vol 1, Chapter 1: Table 58.

Figure 2: Productivity by Size of Farm

available, which does not reward their farming skill. I deviate from the otherwise standard span-of-control framework of Lucas (1978) by allowing skill accumulation in a dynamic environment. This modification serves three purposes. First, it allows calibrating the model to the observed farm size distribution in the U.S, and hence provides reasonable identification of the underlying distribution of idiosyncratic skill types. Second, the model with skill accumulation is consistent with another cross-section data in the U.S. farming sector - older operators operate larger, more productive farms than their younger peers. Table 5 in Appendix shows the evolution of productivity over operator's life cycle is nontrivial. Lastly, this paper stresses the importance of skills, as opposed to distortions, in understanding agricultural productivity differences[9]. In particular, I explore how economic forces affect the accumulative process and hence the agricultural productivity in equilibrium.

To assess model performance, I first calibrate the model to the U.S. economy. Then I ask the model to make quantitative predictions for each country in the sample by varying two country-specific variables: aggregate efficiency and land endowment. The model is able to pick-up almost all of the differences in agricultural productivity, and 80% of the differences in agricultural employment between the 80th percentile and 20th percentile countries. Moreover, the model not only captures the differences in mean farm size across countries, but also generates farm size distributions that are remarkably close to the actual ones for a large set of countries, which is rather surprising given its simple structure.

This paper is related to a large literature that studies cross country income differences, eg., Klenow & Rodriguez-Clare (1997), Prescott (1998), Hall & Jones (1999). Recent de-

[9]The importance of human capital in understanding aggregate productivity differences have been emphasized in Lucas (1988), Manuelli & Seshadri (2005), Erosa *et al.* (2010), among others

velopment in the literature stresses the role played by the agricultural sector in understanding aggregate income differences. Within the level accounting framework, ignoring the dual structure of the economy either results in substantial bias in computed efficiency as in Cordoba & Ripoll (2005) and Chanda & Dalgaard (2008), or disguises the potential gains from eliminating misallocations between sectors, as in Vollrath (2009). Other studies explore the effects of various distortions on agricultural and aggregate productivity within a general equilibrium framework. Restuccia *et al.* (2008) argue that distortions in intermediate inputs are quantitatively important for understanding cross country differences in agricultural and aggregate productivity. Adamopoulos (2006) documents large differences in transportation costs across countries, and show that these differences can account for a sizeable share of income differences. Using a unique micro level data set, Gollin & Rogerson (2010) investigate the role of transportation cost in economic development in Uganda. Unlike these studies, this paper focuses on idiosyncratic productivity of individuals, and how it affects aggregate productivity through self-selection. In this respect, it is similar to Waugh & Lagakos (2010). The authors argue that agricultural productivity is low in poor countries because of poor specialization. However, this paper focuses on differences in the scale of production in the agricultural sector, and uses farm size distribution to discipline the underlying skill distribution. After completing the paper, a recent study by Restuccia & Adamopoulos (2009) was brought to my attention. Both papers focus on farm size heterogeneity across countries and use a version of Lucas' span-of-control model to endogenously generate a size distribution. However, this paper highlights the role of skill accumulation in explaining cross country variation in farm size distribution and agricultural productivity, which is abstracted from in their paper.

The remaining of the paper is organized as follows. In section 2, I describe the model. In section 3, I calibrate the model and discuss the results. Section 4 presents the conclusion.

2 Model

2.1 Environment

Each period a continuum of mass one individuals are born, and live for T periods. Individuals of the same cohort constitute a household, with all decisions made by a hypothetical household head. When born, individuals within a household draw independently their skill type, z, from a known, time invariant distribution $G(z)$. The instantaneous utility function of a household is given by

$$U(c_a, c_n) = \eta \cdot log(c_a - \bar{a}) + (1-\eta) \cdot log(c_n)$$

where (c_a, c_n) denote, respectively, agricultural consumption and nonagricultural consumption *at the household level.* η dictates the relative taste towards two consumption goods. $\bar{a}$ can be interpreted as subsistence consumption level. $\bar{a} > 0$ implies an income elasticity of agricultural consumption less than unity. Each member is endowed with one unit of physical time. Households equally own the stock of land $\bar{L}$. There is no growth in the population nor lifetime uncertainty.

2.2 Household Decision

In this economy, there are two occupations. Each member can either work as a worker or a farm operator. All workers, regardless of skill type, earn the same wage rate. A farm operator combines her skill (z), labor (h_a) and land (ℓ) to produce agricultural output according to

$$Y_a = A \cdot z^{1-\gamma} \left(h_a^{\alpha} \cdot \ell^{1-\alpha}\right)^{\gamma}$$

where A represents the efficiency level. There are competitive rental markets for Labor and land at prices w and q, and output are sold at price p. All prices are expressed relative to the price of nonagricultural output. The residual profit, or return to skill, $\pi(z)$ is retained by the farm operator. It is simple to show

$$\pi(z) = z \cdot (1-\gamma) \cdot (P \cdot A)^{\frac{1}{1-\gamma}} \left(\gamma \left(\frac{\alpha}{w}\right)^{\alpha} \left(\frac{1-\alpha}{q}\right)^{1-\alpha}\right)^{\frac{\gamma}{1-\gamma}}$$

Although the initial realization is drawn exogenously, skill can subsequently grow through investment according to the following technology

$$z_{t+1} = z_t + z_t \cdot s_t^{\theta}$$

where s_t is the fraction of physical time devoted to skill augmentation. Note that this technology assumes time as the sole input. This is done for several reasons. First, it allows for closed-form solutions and clearer expositions. Second, data on time allocations of farm operators are available to discipline relevant parameters. Lastly, data on resources investment by farm operators in skill accumulation are limited, if available at all.

The household head chooses for each member an occupation, which by assumption can not change over time. Then the household head chooses sequences of skill investment and consumption to solve

$$\max: \sum_{t=1}^{T} \beta^t u(c_{at}, c_{nt})$$
$$s.t: \sum_{t=1}^{T} \frac{p_t c_{at} + c_{nt}}{\prod_{\tau=1}^{t} R_\tau} \leq Y$$

where R_τ denotes the interest rate in period $\tau = 1, 2, ..., T$, and Y represents the *maximized* discounted income of the household. The following lemmas establish some results that characterize the stationary equilibrium, where all prices are constant.

Lemma 1 *Workers don't spend time accumulating skills.*

This follows naturally from the assumption that all workers earn the same wage rate w regardless of skill type. Thus it is not optimal for a worker to invest in skill accumulation. Discounted lifetime income of a worker is simply $Y_w = \sum_{t=1}^{T} w \cdot R^{1-t}$. In contrast, since residual profit is strictly increasing in skill input, concavity ensures skill investment profitable for all farm operators. The following lemma characterizes the optimal investment profile of farm operators.

Lemma 2 *Optimal time investment is independent of initial skill type*

The proof is given in Appendix. The lemma implies a common slope of skill profile for all farm operators, and the level is determined by the initial draw. It is convenient to define variable x_t as follows

$$x_t = \begin{cases} 1, & t = 1 \\ x_{t-1} \cdot (1 + s_{t-1}^{\theta}), & t = 2, ..., T \end{cases}$$

$\{x_t\}_{t=1}^{T}$ summarize the level of skill at time t relative to when born for an operator. Clearly, $\{x_t\}$ is independent of type. This allows a simple expression of lifetime discounted income of a type z farm operator

$$Y_f(z) = \pi(z) \cdot \sum_{t=1}^{T} x_t \cdot (1 - s_t) \cdot R^{1-t}$$

Note that $Y_f(z)$ is linear and strictly increasing in skill type z. Recall that discounted lifetime income of a worker (Y_w) is independent of skill type z. This leads to Lemma 3.

Lemma 3 *There exists a cut-off level of skill type, $\bar{z}$, such that household members with skill type $z < \bar{z}$ become workers, and household members with skill type $z \geq \bar{z}$ become farm operators.*

The most able members will operator farms and utilize their skills. The less able members will supply inelastically one unit of labor to the market, and forgo their endowed skills. The marginal operator, whose skill type is $\bar{z}$, is indifferent between two occupations. The maximized discounted income of the household is

$$Y = G(\bar{z}) \cdot Y_w + \int_{\bar{z}} Y_f(z) dG(z) + q \cdot \bar{L}/T \cdot \sum_{t=1}^{T} R^{1-t}$$

2.3 Nonagriculture Firm's Optimization

There is a representative firm that produces nonagricultural output with a linear technology $Y_n = A \cdot H_n$. Two remarks are in order. First, efficiency parameter A augments both agricultural and nonagricultural production, and hence is sector neutral. This technology parameter is intended to capture factors impacting all economic activities within an economy. Second, H_n denotes labor hours and does not embed skills. The representative firm solves

$$\max_{\{H_n\}} \ A \cdot H_n - w \cdot H_n$$

2.4 Equilibrium

A stationary competitive equilibrium is a collection of prices (w, p, q, R), consumption and investment $(c_{at}, c_{nt}, s_t)_{t=1}^{T}$, factor demand $h_a(z), \ell(z), H_n$ such that: (1) given prices, $(c_{at}, c_{nt}, s_t)_{t=1}^{T}$ solve household income maximization problem; (2) given prices, $h_a(z), \ell(z)$ solve farm operator's profit maximization problem, and H_n solve nonagricultural firm's profit maximization problem; (3) Prices are competitive; (4) All markets clear.

To solve the model, I begin by solving for prices (p, q). Equation (1) below states that the type $\bar{z}$ household member must be indifferent between working and operating a farm.

Equation (2) below states the land market clearing condition.

$$\pi(\bar{z}) \cdot \sum_{t=1}^{T} x_t \cdot (1 - s_t) \cdot R^{1-t} = \sum_{t=1}^{T} w \cdot R^{1-t} \tag{1}$$

$$\int_{\bar{z}} \ell(z) dG(z) \cdot \sum_{t=1}^{T} x_t \cdot (1 - s_t) = \bar{L} \tag{2}$$

Dividing (1) by (2) yields an expression of the rental price of land

$$q = \left[\frac{\sum_{t=1}^{T} x_t \cdot (1 - s_t)}{\sum_{t=1}^{T} x_t \cdot (1 - s_t) \cdot R^{1-t}} \right] \cdot \left[\frac{\gamma \cdot (1-\alpha) \cdot \left(\sum_{t=1}^{T} w \cdot R^{1-t} \right)}{(1-\gamma) \cdot \bar{L}} \right] \cdot \frac{\int_{\bar{z}} z dG(z)}{\bar{z}} \tag{3}$$

Substituting (3) into (1) yields the relative price of agricultural good

$$p = \left[\frac{\sum_{t=1}^{T} w \cdot R^{1-t}}{\bar{z} \cdot (1-\gamma) \cdot \sum_{t=1}^{T} x_t \cdot (1 - s_t) \cdot R^{1-t}} \right]^{1-\gamma} \cdot \left(\gamma \left(\frac{\alpha}{w} \right)^{\alpha} \left(\frac{1-\alpha}{q} \right)^{1-\alpha} \right)^{-\gamma} \cdot \frac{1}{A} \tag{4}$$

Note the relative price of agricultural good is strictly decreasing in the cut-off type $\bar{z}$ and aggregate TFP. Solving for optimal consumption bundles and aggregating over generations yields the aggregate demand of two consumption goods

$$C_a = \sum_{t=1}^{T} c_{at} = \left[\sum_{t=1}^{T} (\beta R)^{t-1} \right] \cdot \left[\frac{Y - p \cdot \bar{a} \sum_{t=1}^{T} R^{1-t}}{\sum_{t=1}^{T} \beta^{t-1}} \right] \cdot \frac{\eta}{p} + T \cdot \bar{a} \tag{5}$$

$$C_n = \sum_{t=1}^{T} c_{nt} = \left[\sum_{t=1}^{T} (\beta R)^{t-1} \right] \cdot \left[\frac{Y - p \cdot \bar{a} \sum_{t=1}^{T} R^{1-t}}{\sum_{t=1}^{T} \beta^{t-1}} \right] \cdot (1 - \eta) \tag{6}$$

Detailed derivations are given in appendix.

In each household, the measure of workers is $G(\bar{z})$. Given constant prices, the division of labor does not change across cohorts. Hence the total measure of worker is simply $T \cdot G(\bar{z})$. The measure of workers demanded in agricultural production is $H_a = \left[\sum_{t=1}^{T} x_t (1 - s_t) \right] \cdot \int_{\bar{z}} h_a(z) dG(z)$. Imposing labor market clearing, the measure of workers in the nonagricultural sector is $H_n = T \cdot G(\bar{z}) - H_a$. The output in the nonagricultural sector is $Y_n = A \cdot H_n$. In the agricultural sector, aggregating production over farmers yields aggregate production $Y_a = \left[\sum_{t=1}^{T} x_t (1 - s_t) \right] \cdot \int_{\bar{z}} y_a(z) dG(z)$. Good markets clearing conditions requires $C_a = Y_a, C_n = Y_n$. By Walras'law, loan market clears as well.

In the standard Lucas' span-of-control model, threshold skill level is independent of TFP. In this model, however, threshold level increases with TFP. This highlights the main mechanism through which the model is able to reconcile high labor share and low labor productivity in agriculture of low income countries. Low TFP transforms into low wage payment, and hence renders farming more lucrative for even low skill household members, because the price of agriculture output rises more than proportionately to offset the decline in TFP. Employment in agriculture increases, yet average skill, and hence productivity, decreases. To see this, consider two economies with two efficiency levels A_r, A_p. In addition assume that $A_r = g \cdot A_p$ with $g > 1$. The former can be interpreted as a typical rich country, and the latter a poor one. Holding land endowment fixed, the model predicts a lower skill threshold and a higher interest rate in the poor country. For a simple proof, assume the threshold level of skill and interest rate are the same. From equation (3), it is straight forward to see that $q_r = g \cdot q_p$. Given this, equation (4) implies $p_r = p_p$. These two conditions, together with equation (5), further implies $Y_r = g \cdot Y_p$, i.e., aggregate income is proportional to aggregate TFP. Aggregate production of agricultural good is also proportional to TFP. However, with nonhomothetic preferences, demand of agricultural consumption drops by less than a factor of g in the poor economy, as suggested by equation (5). Excess demand pushes up the price of agricultural consumption, and reduces the threshold level of skill. This implies a higher labor share and lower productivity in the agricultural sector. Influx of labor into the agricultural sector also reduces the supply of nonagricultural good and bids up the equilibrium interest rate.

3 Calibration and Results

In this section, I parameterize the model. Model period is 10-years. Individuals are born at the age of 25 and live for 5 periods. Assuming an annual discount rate of 0.96, I set $\beta = 0.96^{10}$. TFP for the U.S is normalized to be 1. Parameters in the agricultural production function are directly inferred from agriculture value added data of the U.S. (see Appendix 5.3). Over the period 1980-1999, the average share of output accruing to operators is 20%. I thus set $\gamma = 1 - 0.2 = 0.8$. This parameter is critical to the quantitative implications of the model, and deserves some discussions here. This paper is certainly not the first one to estimate the span-of-control parameter, though most studies either assume a one-sector framework or focus on the nonagricultural part of the economy. For studying the effects of size-dependent policies on aggregate output, Guner *et al.* (2008) estimate the span-of-control parameter to be 0.8 for the aggregate economy. A similar value is used in Restuccia & Rogerson (2008) for studying the effects of idiosyncratic distortions at the plant level on aggregate output. For the manufacturing sector alone, Atkeson & Kehoe (2005) obtain an estimate of 0.85. A value of 0.8 for the agricultural sector appears roughly in line with these estimates[10]. Over the same period, return to land and labor are almost identical, which suggests $\alpha = 0.5$ is a consistent value.

I restrict the skill type distribution to be lognormal with mean μ and standard deviation σ. This leaves 5 parameters $(\bar{a}, \eta, \bar{L}, \mu, \sigma, \theta)$ to be chosen simultaneously to match moments of the U.S. economy. From World Development Indicator, agriculture employs 2% of the labor force. I also target a long run agricultural employment share of 0.5%. This corresponds to the asymptotic agricultural employment share when the subsistence consumption share of income is effectively zero. To discipline θ, I turn to data on time allocations of farm operators. Census of Agriculture reports the number of days *off* the farm for operators in 5 different age groups: 25-34, 35-44, 45-54, 55-64, 65+. From there I compute the total working days, as well as the fraction supplied by operators in different age groups (see Appendix 5.4). Within the model, this statistic corresponds to $\frac{1-s_i}{\sum_{i=1}^{T} 1-s_i}$ because operators of generation i spend $(1-s_i)$ fraction of their time in farm production. I choose θ to reproduce the share of operators aged 35-44. However, the implied shares of other operators are close to data as well[11]. The model is also asked to reproduce the observed size distribution of farms in the U.S.. Figure 3 plots the calibrated size distribution against data. By construction, the model generated size distribution matches the data well. In addition, as depicted in Figure 4 in Appendix, the model also implies a land size distribution that fits the data very well, even though it is not targeted. The model also generates a distribution of hired labor over size classes that is reasonably close to the data [12]. Parameter values are summarized in Table 6 in Appendix.

3.1 Quantitative Experiment

In this section I assess the model's ability to quantitatively explain cross-country variations in agricultural productivity. Data on sectoral productivity, sectoral labor shares and land endowment are from Restuccia et al. (2008). The size distributions of farms are constructed

[10] Restuccia & Adamopoulos (2009) use a smaller value $\gamma = 0.6$, but they do not include hired labor in their production function.

[11] See Table 7 in Appendix

[12] See Figure 5 in appendix. Hired labor is inferred using expenditure data assuming homogenous wage rate across farms of different sizes.

from the World Census of Agriculture (round 1990, 2000) published by Food and Agriculture Organization of the United Nations. These two data sets, however, are not directly comparable because of time period differences. The data in Restuccia et al. (2008) pertain to the year 1985. World Census of Agriculture is a collection of national agriculture censuses conducted independently in each member country - possibly at different points of time (see Table 10 for country specific census years). In principle, this study should be restricted to countries where the agriculture census was conducted in 1985. As a first pass, however, I merge these two data sets to obtain a sample of 40 countries with two defenses. First, census of agriculture is conducted every 5 years in most countries, if at all available. It is thus rather costly to obtain completely synchronized data set as detailed as the present one. Second, even though census year in the sample ranges from 1980 to 2000. Most of the countries indeed have their censuses conducted around 1990. The quantitative implications of the model remain reasonable provided the composition of farms do not undergo drastic changes over 5 years.

I test the model's predictive ability by varying two country specific variables: the level of TFP (A) and land endowment ($\bar{L}$). All countries are otherwise identical. In particular, they all face the same *ex-ante* distribution of skill types. Country specific A_i and $\bar{L}_i$ are inferred as follows

$$A_i = \frac{ynln_i}{ynln_{us}}, \qquad \bar{L}_i = \frac{LER_i}{LER_{us}} \cdot \bar{L}_{us}$$

where $ynln_i$ is the Nonagricultural GDP per worker of country i, and LER_i is the Land-employment ratio of country i. Both are directly available from Restuccia et al.(2008).

To assess the quantitative performance of the model, I focus on the following metrics: agricultural labor share (La), real agricultural output per worker (ryala), real GDP per worker (rgdp) and mean farm size (mfs). Note that agricultural employment includes both workers working in the agricultural sector and farm operators. U.S price is used as international price when computing aggregate output to make results comparable to the data, which is PPP adjusted. To facilitate comparison between model predictions and the data, I divide countries in the sample into quintile by GDP per worker in the data. Productivity in the richest quintile (Q.5) is normalized to be 1. The sample consists of 40 countries with good representation of both developed and developing nations[13]. The results are summarized in

[13]Burkina Faso, Egypt, India, Sri Lanka, Morocco, Uganda, Dominica, Pakistan, Ivory Coast, Greece, Hungary, Italy, Tunisia, Switzerland, Portugal, Ecuador, Peru, Netherland, Belgium, Spain, Colombia, Nicaragua, Ireland, Austria, Germany, France, Denmark, Venezuela, United Kingdom, Finland, Brazil,

Table 1.

Quintile	rgdp		ryala		L_a		mfs	
	Data	Model	Data	Model	Data	Model	Data	Model
Q.1	0.13	0.19	0.04	0.04	0.66	0.48	7	16
Q.2	0.30	0.35	0.15	0.12	0.34	0.22	56	43
Q.3	0.52	0.59	0.36	0.37	0.18	0.07	83	107
Q.4	0.85	0.87	0.82	0.48	0.08	0.05	68	69
Q.5	1.00	1.00	1.00	1.00	0.05	0.05	515	381

Table 1: Model vs Data, by Income Quintile

The model does an excellent job explaining productivity differences. In the sample, the richest (Q.5) countries are about 8 times more productive overall and 25 times more productivity in agriculture, relative to the poorest countries (Q.1). The model generates almost the same magnitude of differences. As pointed out in the introduction, agricultural productivity is viewed to be determined by two forces: overall efficiency and idiosyncratic productivity of farmers. In the data, aggregate TFP - as inferred from nonagricultural productivity, differs by at most a factor of 5 between the richest and poorest countries. Hence, the first force accounts for about 50% of the differences in agricultural productivity. The differences in idiosyncratic productivity of farmers explain the remaining half. Outside the two ends of the world income distribution, the model explains the productivity differences reasonably well - an notable exception is high income countries (Q.4), for which the model substantially underpredicts their agricultural productivity[14].

High employment and low labor productivity in agriculture are jointly driving low income. It is thus important for the model to be consistent with data in terms of sectoral labor allocation. For the top quintile countries, the model correctly predicts the employment share in agriculture. For the bottom quintile countries, the model predicts a 48% agricultural employment share - about 80% of the actual share. For low income countries (Q.2), the model also predicts a lower agricultural labor share, compared to the data. This reflects other forces at work. For example, high price of intermediate inputs, as discussed in Restuccia et al. (2008), induces farm operators to substitute labor for modern input. This model also abstracts from labor market distortions, while in low income countries barriers to sectoral labor movements are common as evidenced by substantial gap in earnings. One famous example is the *Hukou* system in China that imposes institutional restriction on immigration

Chile, Norway, Sweden, New Zealand, Canada, Uruguay, Argentina, Australia, United States

[14]Low land endowment and a relatively large elasticity of land are responsible for the counterfactual prediction

from rural villages to urban cities. My results show that these distortions are also important for understanding sectoral labor allocations.

The model also generates increasing mean farm size with income level, as observed in the data. One important feature of this model is its ability to reproduce not only the mean farm size, but also the entire *farm size distribution* across countries. In Appendix I plot the model predicted farm size distributions along with their empirical counterparts for all countries in the sample. Even though *ex ante* all countries face the same skill-type distribution, the *ex post* size distribution of farms exhibits substantial variations across levels of income. For a large set of countries the model generated size distributions are amazingly close to the data, which I view as a success of the model.

One stylized fact regarding economic development is the declining importance of agriculture in aggregate output - one available measure is agriculture value added as a percentage of GDP. For the top quintile countries, the model predicts agricultural output to be 10% of the aggregate output, while in the data it is 3%. For the bottom quintile countries, the model predicts the value to be 70%, substantially higher than 30% in the data. Hence the model captures correctly the declining share with income but fails to generate the exact levels. Another testable aspect of the model is its prediction of the relative price of agricultural output. A central prediction is that the relative price is higher in low income countries. Using ICP data from the World Bank, I compute the relative price between "agricultural consumption" and "nonagricultural consumption" for all available countries[15]. The relative price in 2005 is around 4 times higher in the 10th percentile country, compared to the 90th percentile country. Moreover, the model predicts the relative price to be about 2.8 times higher in the poorest countries, which is roughly in line with the data.

Recall that in the model, countries are different in two dimensions: TFP and land endowment. Which exogenous variable is relatively more important in determining productivity? To shed light on this question, I perform a series of counterfactual experiments for a hypothetical country that represents the poorest countries in the sample[16]. Relative to the U.S, the representative poor country has 4.5 times lower TFP, and 2.1 times smaller land endowment. To disentangle the relative contribution, I change one exogenous variable at a time. Table 2 summarizes the results.

If the inferred TFP is maintained at the U.S. level, and land endowment is reduced by

[15] "Agricultural consumption" is defined as food, non-alcoholic beverage, alcoholic beverage and tobacco. "Nonagricultural consumption" is defined as the rest of individual consumptions plus capital consumption. A similar calculation is done also in Waugh & Lagakos (2010)

[16] These countries are Burkina Faso, Uganda, India, Ivory Coast and Pakistan

Exg. variable	L_a	ryala	mfs
$\bar{L}$ only	2.5%	1/2	117
A only	24%	1/22	47
Both A and $\bar{L}$	53%	1/48	13
Data	70%	1/51	3

Table 2: TFP versus Endowment

half, equilibrium labor allocation and productivity change minimally, though mean farm size drops by roughly a half. Differences in endowment alone can't go far in explaining agricultural labor share and productivity differences. In contrast, if inferred TFP is reduced - with land endowment unchanged, there is a massive movement of labor into the agricultural sector. Moreover, agricultural productivity drops by a factor of 22, and mean farm size drops further to 47 hectares. TFP thus has a more profound impact on equilibrium allocations. It is also interesting to note that the decomposition of TFP and land endowment is not orthogonal. If both TFP and land endowment are reduced, the representative poor country allocates 53% of the labor force to agriculture. Output per worker drops massively - by a factor of 48. An average farm is only about one tenth the size of an average farm in the U.S..

3.2 Discussion

A novel and crucial feature of the model is to embed skill accumulation in an otherwise standard Lucas' span-of-control model. A similar idea was illustrated in Bhattacharya (2009), who shows that skill accumulation is critical to quantitatively explain cross-country variation in firm size distribution and income. While in that paper the main channel of variation is coming from resources input in skill accumulation, in this model the main mechanism operators through nonhomothetic preferences. To investigate the quantitative importance of skill accumulation, I calibrate a version of the model without skill accumulation, and then assess its quantitative prediction for the representative poor country. The model without skill fails to generate the observed size distribution of farms in the U.S., although it can reproduce the first moment. Moreover, given exogenous variables, the model without skill accumulation in general explains less of the cross-section differences in labor allocation and productivity. Details of calibration and results are postponed in Appendix.

As shown in Restuccia *et al.* (2008), barriers to intermediate inputs have sizeable impact on labor allocation and productivity. That paper assumes a representative household. Here I explore how barrier to intermediate inputs affect agricultural productivity in an environment with idiosyncratic farmers. To do so, I modify the agricultural production technology to incorporate intermediate input X

$$Y_a = A \cdot z^{1-\gamma} \left(X^{\phi} \cdot h^{\rho} \cdot \ell^{1-\phi-\rho} \right)^{\gamma}$$

As in Restuccia et al. (2008), one unit of nonagricultural output can be consumed or converted into intermediate good at the rate of π. There is a linear technology producing nonagricultural output. For expositional purposes, I suppress skill accumulation to disentangle the effects coming from distortions from those stemming from skill investment. Detailed calibration and results are given in Appendix. As expected, the model explains more of the differences in labor allocation and productivity when distortion in intermediate inputs are included (58% vs. 48% in labor share, 33-fold vs. 28-fold differences in agricultural productivity). Moreover, high price of intermediate inputs also reduces the mean farm size.

Several remarks on the limitations of the model are in order here. Firstly, land endowment is approximated by land-employment ratio, and hence abstracts from possible differences in the quality of land. Moreover, the calibrated share of land in agriculture production is considerably large, compared to the common values used in the literature[17]. Secondly, TFP level is mapped into nonagricultural output per worker. While this approach appears reasonable for rich countries where minimum resources are devoted to the agricultural sector, it is deemed less appropriate for poor countries where most of the economic activity takes place in the traditional sector.

4 Conclusion

In this paper I develop a model that links agricultural productivity to the skills of farm operators. In poor countries, subsistence need and low wage rate renders farming a better option for even low skill individuals. As a result of self-selection, a large fraction of the labor force work in the traditional sector. Moreover, the average farm operator has low skill and hence low measured labor productivity. The calibrated model can explain most of the observed differences in agricultural productivity and labor employment. By allow skill accumulation in an otherwise standard Lucas' span-of-control framework, the model is able to capture not only the differences in the mean farm size, but also the variation in the *size*

[17] Griliches (1964) estimates the share to be around 16% for the U.S., though his estimates are for the period round 1950. For a cross-section, Hayami & V.W.Ruttan (1970) estimates the share of land to be in a ball park of 10%. Hansen & Prescott (2002) uses a land share of 30% for the technology in the Malthus era.

distribution across countries.

The agricultural sector characterized in this paper is "poor but efficient", as articulated in Schultz (1964). This contrasts with studies that point to various distortions as explanations of low agricultural productivity in poor countries. Instead, this paper stresses the importance of skills in understanding sectoral productivity patterns, and hence provides an alternative view of the observed cross-country differences in agricultural productivity.

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A Data Appendix

- **World Census of Agriculture:** The data is available through the link http://www.fao.org/economic/ess/world-census-of-agriculture/main-results-by-coun

- **Return to Operator in U.S Farming:** This is computed from agriculture value added data accessible from United States Department of Agriculture (http://www.ers.usda.gov/Data/FarmIncome/FinfidmuXls.htm).

  Total output(YA), is the summation of crop production, livestock production and revenues from services and forestry. Total output, net of government transfers, are fully dissipated into Purchased Inputs (PI), Capital Consumption plus Real Estate and Non Real Estate Interest (CCI), Compensation to Hired Labor (CHL), Net Rent Received by Non-operator Landlord (RL) and Net Farm Income (NFI), i.e.,

$$YA = PI + CCI + CHL + RL + NFI$$

  Here I implicitly assume that real estate and non real estate interest income are capital income because structures are typically considered as a component of capital. Net farm income represents " entrepreneurial earnings of those individuals who share in the risks of production and materially participate in the operation of the business", and thus captures the return to skills provided by farm operator. For the period 1980-1999, the estimated income are given in the table blow.

	1985	1980-1990	1990-1999	1980-1999
Intermediate	0.47	0.48	0.51	0.49
Capital	0.24	0.24	0.15	0.20
Labor	0.05	0.05	0.07	0.06
Land	0.05	0.04	0.05	0.04
Operator	0.18	0.18	0.23	0.20

Table 3: Factor Shares in U.S. Farming

- **Working Days by Age of Farm Operator:** From 1992 census of agriculture, I extract the number of days *not* working on the farm for farm operators by age (Panel A). To compute the the hours supplied by operator of a certain age, I assume 250 working days a year. In addition, I use the midpoint of the interval as the average days off farm. For example, "None" in the table means operators work 250 days a year.

Operators work 200 days if in interval " 1-99 days", 150 working days if in interval "100-199 days", and 25 working days if in interval "200 days+". This allows me to compute the total number of working days a year for operators in any age category. Finally, I compute the share of days supplied by operators in age group i (Panel B) as $s_i = \frac{wd_i}{\sum_{i=1}^{I} wd_i}$, where wd_i is the number of working days for operators in age group i.

Panel A						
	25-34	35-44	45-54	55-64	65+	Total
None	52,938	104,375	110,380	158,629	249,512	675,834
1-99 days	18,015	29,804	25,428	27,061	19,267	119,575
100-199 days	7,872	14,648	14,308	12,423	6,169	55,420
200 days +	10,028	15,565	14,681	11,082	5,087	56,443
Panel B						
Work Days (1000s)	17875	33908	34478	46589	66975	
% Days	0.09	0.17	0.17	0.23	0.34	

Table 4: Days off Farm by Age of Operator

- **Scale and Productivity By Age of Farm Operator:** The following table is restricted to farm operators whose primary occupation is farming. Mean holding size is measured by acreage per farm. Productivity is measured by net cash income of operators.

Age	25-34	35-44	45-54	55-64	65+
Mean Holding Size	575	857	909	736	542
Net Cash Income	59,839	90,705	91,501	60,249	32,282

Source: 2007 U.S. Census of Agriculture, Vol 1, Chapter 1: Table 63.

Table 5: Scale and Productivity over Life Cycle of Farm Operators

B Model Appendix

B.1 Proofs

Proof of Lemma 1 *It is useful to first derive the profit function, where* $\Pi(z) = \max_{h,\ell} \;\; py - wh - ql$*. Using F.O.C, it is easy to show that*

$$\pi(z) = \tilde{\pi} \cdot z$$
$$\textit{where} \;\; \tilde{\pi} = (1-\gamma)\cdot(P\cdot A)^{\frac{1}{1-\gamma}} \left(\gamma\left(\frac{\alpha}{w}\right)^{\alpha}\left(\frac{1-\alpha}{q}\right)^{1-\alpha}\right)^{\frac{\gamma}{1-\gamma}}$$

Profit function is thus linear in ability z. In a stationary equilibrium, prices are constant over time. This implies constant profit per unit of skill. Thus farm operator's problem can be written as one that maximizes the sum of discounted lifetime skill.

$$\max_{s_t} : \sum_{t=1}^{t=T} R_t^{1-t} \cdot z_t \cdot (1-s_t)$$
$$s.t : z_{t+1} = z_t(1+s_t^{\theta})$$

Let λ_t *be the Lagrangian multiplier for period t*

$$\mathcal{L} = \sum_{t=1}^{T} R^{1-t} \cdot z_t \cdot (1-s_t) - \lambda_t(z_{t+1} - z_t(1+s_t^{\theta}))$$

F.O.Cs are

$$R^{1-t} = \lambda_t \theta s_t^{\theta-1} \tag{7}$$
$$\lambda_t = R^{-t}(1-s_{t+1}) + \lambda_{t+1}(1-\delta_t + s_t^{\theta}) \tag{8}$$

From equation(9), if λ_{t+1} *is independent of beginning of period skill* z_t*, then* (λ_t) *does not depend on* z_t*. Consequently the equation (8) the optimal time investment* s_t *does not depend on* z_t *as well. To solve the optimal path, I use backward induction. Clearly, it is optimal to invest no time in the last period,* $s_T = 0, \lambda_T = 0$*, and hence independent of* z_{T-1}*. Using the above argument,* λ_{T-1} *and* s_{T-1} *does not depend on* z_{T-1}*. Repeating this argument implies that the entire path of investment is independent of initial skill type.*

Proof of Lemma 2 *Life time budget constraint can be written as*

$$\sum_{t=1}^{T} \frac{pc_{at} + c_{nt}}{R^{t-1}} \leq Y$$

where Y is the discounted lifetime income. The Lagrangian is

$$\mathcal{L} = \sum \beta^t(\eta log(c_{at} - \bar{a}) + (1-\eta)log(c_{nt})) - \lambda \left[\sum \frac{pc_{at} + c_{nt}}{R^{t-1}} - Y\right]$$

F.O.C yields

$$\frac{\beta^t \eta}{c_{at} - \bar{a}} = \lambda \frac{p}{R^{t-1}} \tag{9}$$

$$\frac{\beta^t(1-\eta)}{c_{nt}} = \lambda \frac{1}{R^{t-1}} \tag{10}$$

(1) divided by (2) yields the intratemporal allocation between two consumption goods as

$$\frac{p(c_{at} - \bar{a})}{c_n t} = \frac{\eta}{1-\eta}. \tag{11}$$

Iterating (1) and (2) one more period yields the usual intertemporal allocations

$$(c_{a,t+1} - \bar{a}) = \beta R(c_{at} - \bar{a}) \tag{12}$$

$$c_{n,t+1} = \beta R c_{nt} \tag{13}$$

Substitute F.O.C into budget constraints we have

$$\sum_{t=1}^{T} \frac{p\left[\cdot(c_{a1} - \bar{a}) \cdot (\beta R)^{t-1} + \bar{a}\right] + (\beta R)^{t-1} \cdot c_{n1}}{R^{t-1}} = Y$$

$$\rightarrow p \cdot (c_{a1} - \bar{a}) + c_{n1} = \frac{Y - p \cdot \bar{a} \sum_{t=1}^{T} R^{1-t}}{\sum_{t=1}^{T} \beta^{t-1}}$$

$$\rightarrow c_{a1} = \eta \cdot \frac{Y - p \cdot \bar{a} \sum_{t=1}^{T} R^{1-t}}{\sum_{t=1}^{T} \beta^{t-1}} / p + \bar{a}$$

$$c_{n1} = (1-\eta) \cdot \frac{Y - p \cdot \bar{a} \sum_{t=1}^{T} R^{1-t}}{\sum_{t=1}^{T} \beta^{t-1}}$$

Aggregate consumption at a point of time is given by

$$C_a = \sum_{t=1}^{T} c_{at} = \left[\sum_{t=1}^{T} (\beta R)^{t-1} \right] \cdot \left[\frac{Y - p \cdot \bar{a} \sum_{t=1}^{T} R^{1-t}}{\sum_{t=1}^{T} \beta^{t-1}} \right] \cdot \frac{\eta}{p} + T \cdot \bar{a}$$

$$C_n = \sum_{t=1}^{T} c_{nt} = \left[\sum_{t=1}^{T} (\beta R)^{t-1} \right] \cdot \left[\frac{Y - p \cdot \bar{a} \sum_{t=1}^{T} R^{1-t}}{\sum_{t=1}^{T} \beta^{t-1}} \right] \cdot (1 - \eta)$$

B.2 Development Accounting Exercise

To simply the calculation, I assume that all farms in size class $[s_l, s_h]$ have the same size $(s_l + s_h)/2$. Let s_i denote the mean farm size, and μ_i denote the corresponding share in class i. In addition, let y_i and h_i denote, respectively, the output and labor. Using U.S. data, I estimate the following equations

$$log\left((y/h)_i\right) = b1 + b2 \cdot log(s_i)$$
$$log\left((hl)_i\right) = c1 + c2 \cdot log(s_i)$$

Note that y_i is measured by *the total market sales of goods net of government payments*, and h_i is measured by the *sum of farm operators and hired workers.* The methodology in U.S. agriculture census assumes one farm operator per farm. Let n_i note the number of farms report hired labor, and let hl_i denote the number of hired labor, the total number of worker in size class i is simply $n_i + hl_i$. For 2007, the estimated coefficients are (b1, b2) = (-0.916,0.548) and the R^2 is 93% for the first regression. For the second regression, the estimated coefficients are (c1, c2) = (1.62, 0.058) and the R^2 is 72%. Given size distribution μ_i over size class, then aggregate output *per worker* is computed as

$$Y = \sum_i \left[(b1 + b2 \cdot log(s_i)) \cdot h_i \cdot \mu_i \right]$$
$$h_i = \frac{(c1 + c2 \cdot log(s_i)) \cdot \mu_i + \mu_i}{\sum_i \left[(c1 + c2 \cdot log(s_i)) \cdot \mu_i + \mu_i \right]}$$

where the second equation gives the distribution of workers over size classes.

To compare against data, I compute the log-variance ratio as $\frac{var(log(Y_{model}))}{var(log(Y_{data}))}$. The numerator is the variance of logarithm of agricultural productivity in the model. The denominator is the variance of logarithm of agricultural productivity in the data. For the current sample, this ratio is 26.5%.

B.3 Parameter Values

η	$\bar{a}$	θ	$\bar{L}$	μ	σ
0.015	0.221	0.3157	0.7842	-3.1236	4.1693

Table 6: Parameter Values

Age	25-34	35-44	45-54	55-64	65+
Data	0.09	0.17	0.17	0.23	0.34
Model	0.08	0.16	0.21	0.26	0.29

Table 7: Time Share by Age of Operator: Model against Data

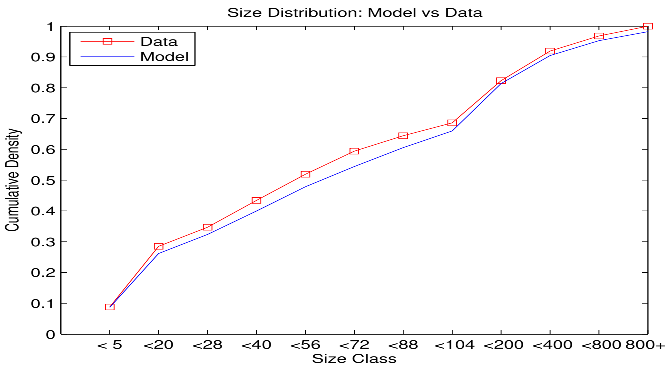


Figure 3: Calibrated Size Distribution

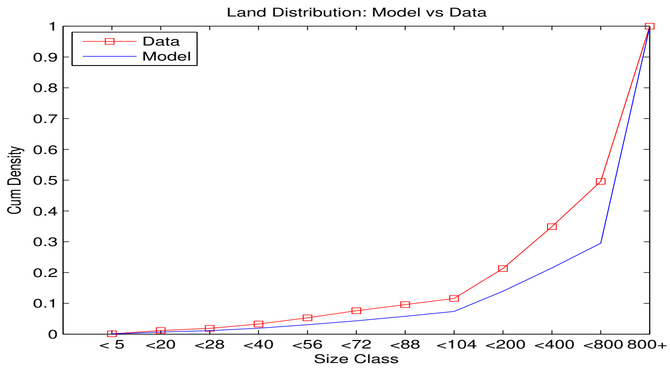


Figure 4: Implied Distribution of Land

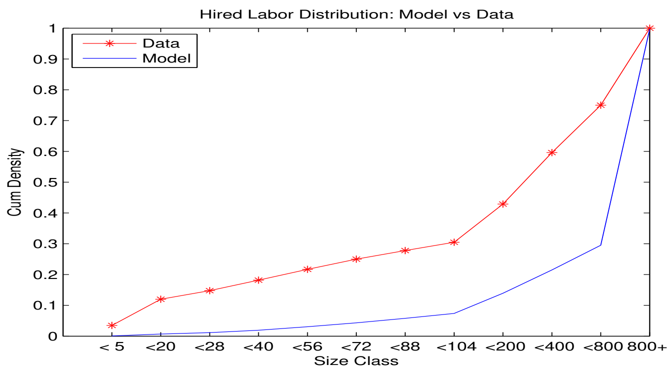


Figure 5: Implied Distribution of Hired Labor

B.4 Model Performances

1. Baseline Model Prediction

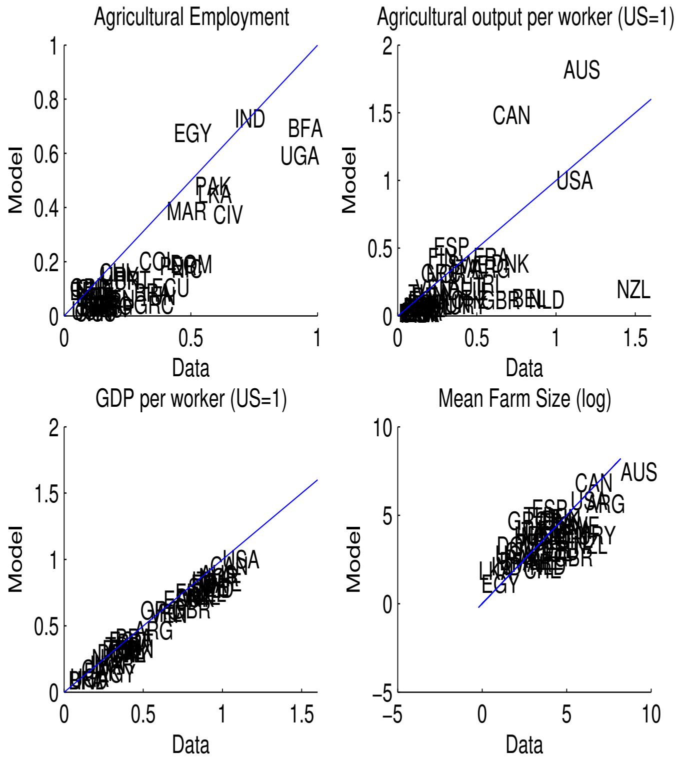


Figure 6: Model Prediction Against Data

2. Model without Skill Accumulation

I calibrate $(\eta, \bar{a}, \mu, \sigma)$ to match: current agricultural employment (2%), long run agriculture employment (0.5%), Mean farm size (178) and coefficient of variation of farm size distribution (0.5). I ask the model to predict for a representative poor country with 4.5 times lower TFP and a 2.1 times smaller land endowment.

3. Model with Intermediate Inputs

I set $\gamma = 0.8$, $\phi = 0.5$ and $\rho = 0.2$. For the U.S, $\pi = 1$. I choose $(\eta, \bar{a}, \mu, \sigma)$ to target a 2% current agriculture employment, 0.5% long run agriculture employment, 2% share

Exg. variable	L_a	ryala	mfs
$\bar{L}$ only	3.3%	1/1.6	65
A only	26%	1/16	20
Both A and $\bar{L}$	48%	1/28	6
Data	70%	1/51	3

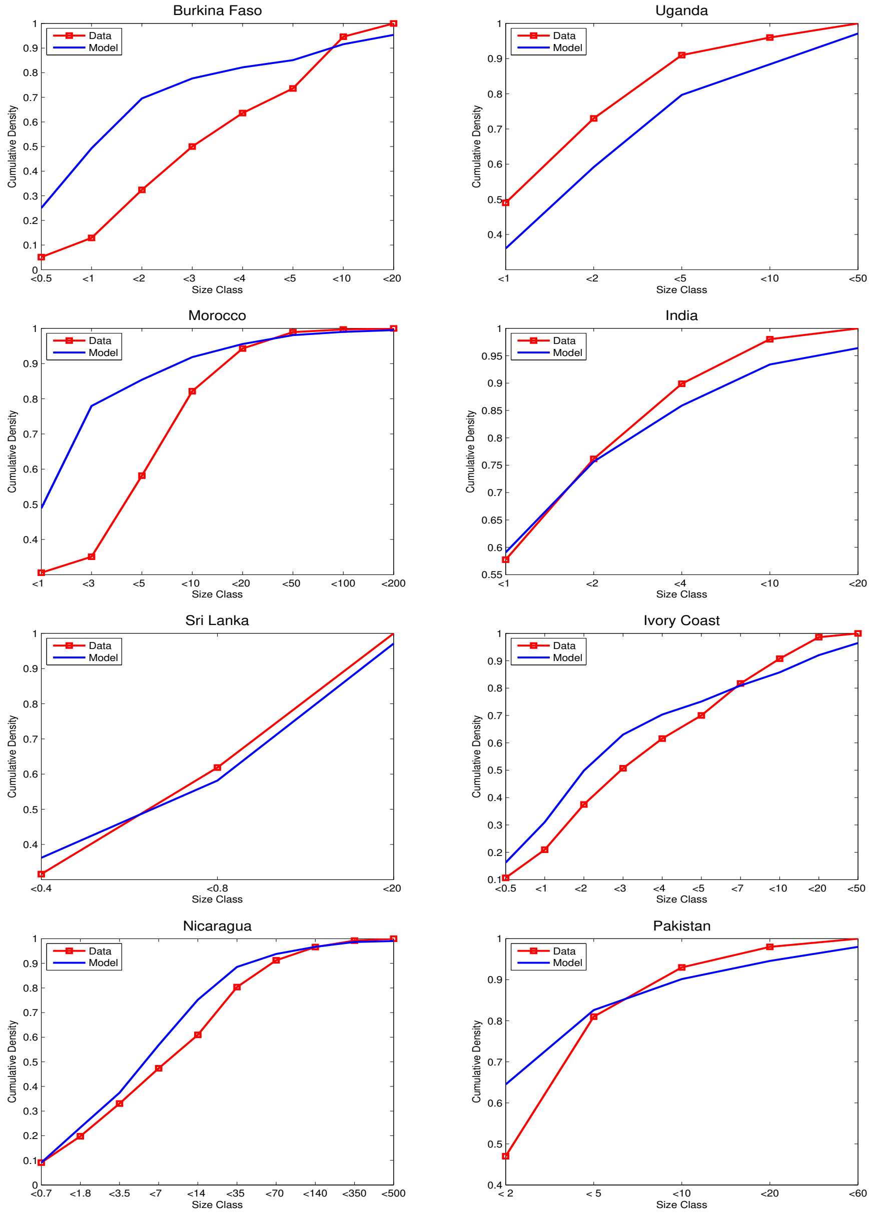
Table 8: TFP versus Endowment (No Skill Accumulation)

of agriculture output of GDP, and the mean farm size. Again I ask the calibrated model to predict equilibrium allocations for the representative poor country, which has 4.5 times lower TFP, 2.1 times smaller land endowment and 3 times higher relative price of intermediate inputs.

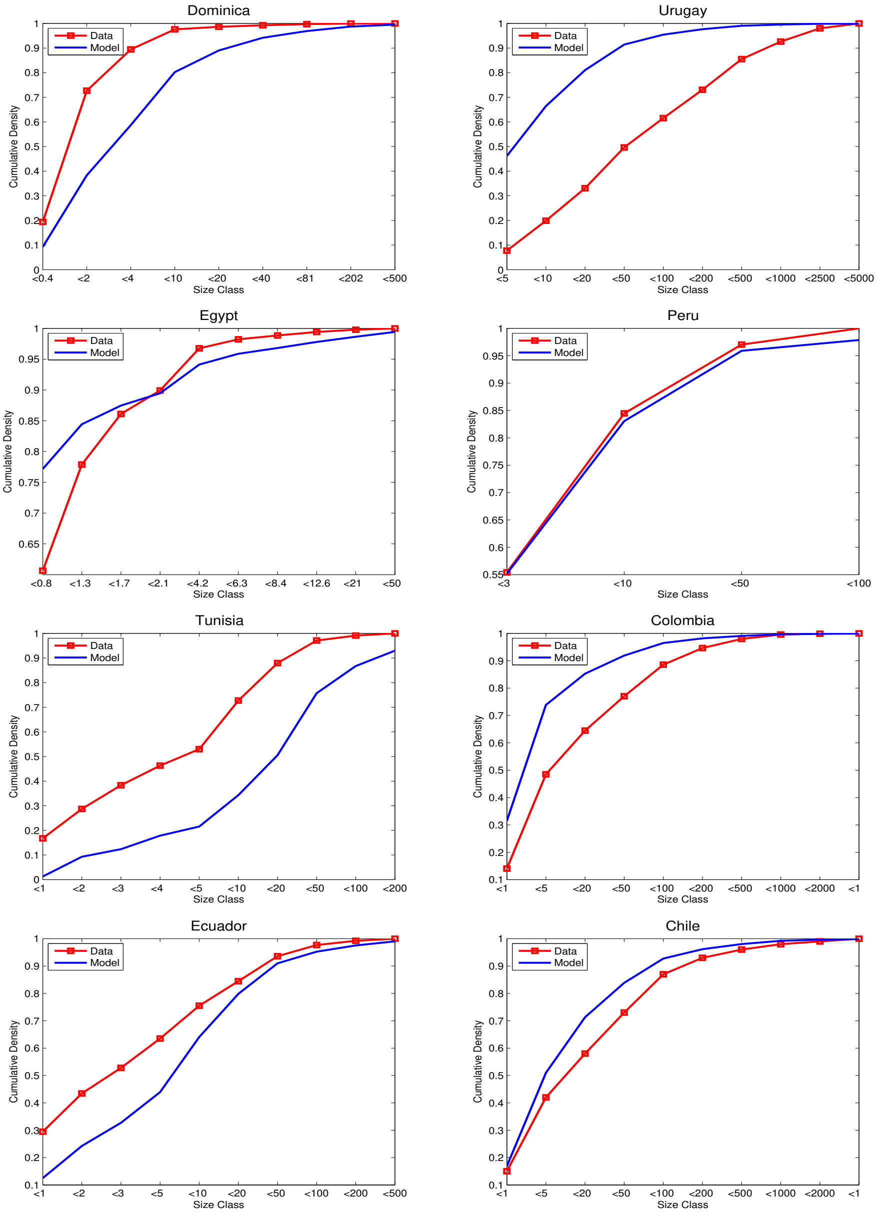
Exg. variable	L_a	ryala	mfs
$\bar{L}$ only	2.4%	1/1.2	88
A only	29%	1/17	18
π only	3.1%	1/1.6	135
A and $\bar{L}$	34%	1/20	7
A and π	49%	1/28	12
π and $\bar{L}$	3.6%	1/1.9	57
A, π and $\bar{L}$	58%	1/33	5
Data	70%	1/51	3

Table 9: TFP versus Endowment (With Intermediate)

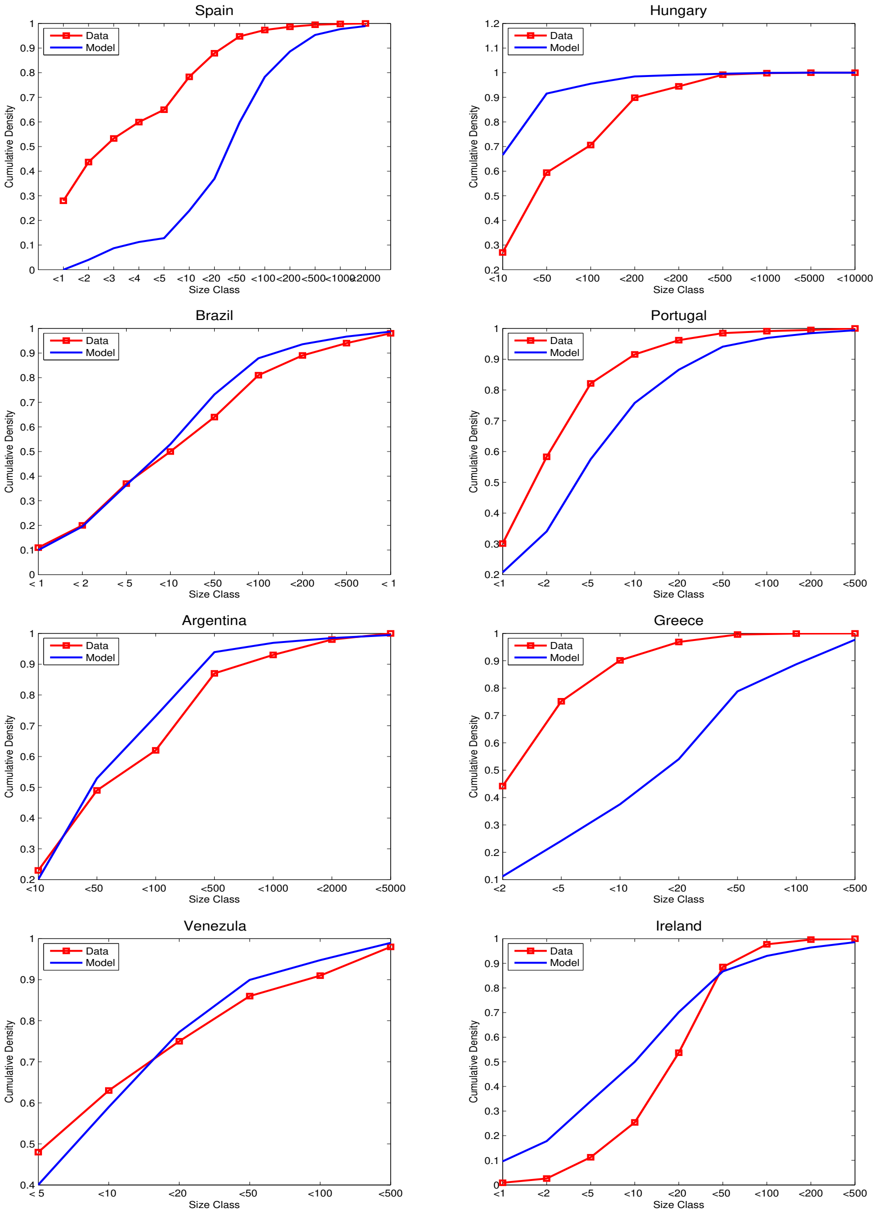
B.5 Model Predicted Farm Size Distribution (Q.1)



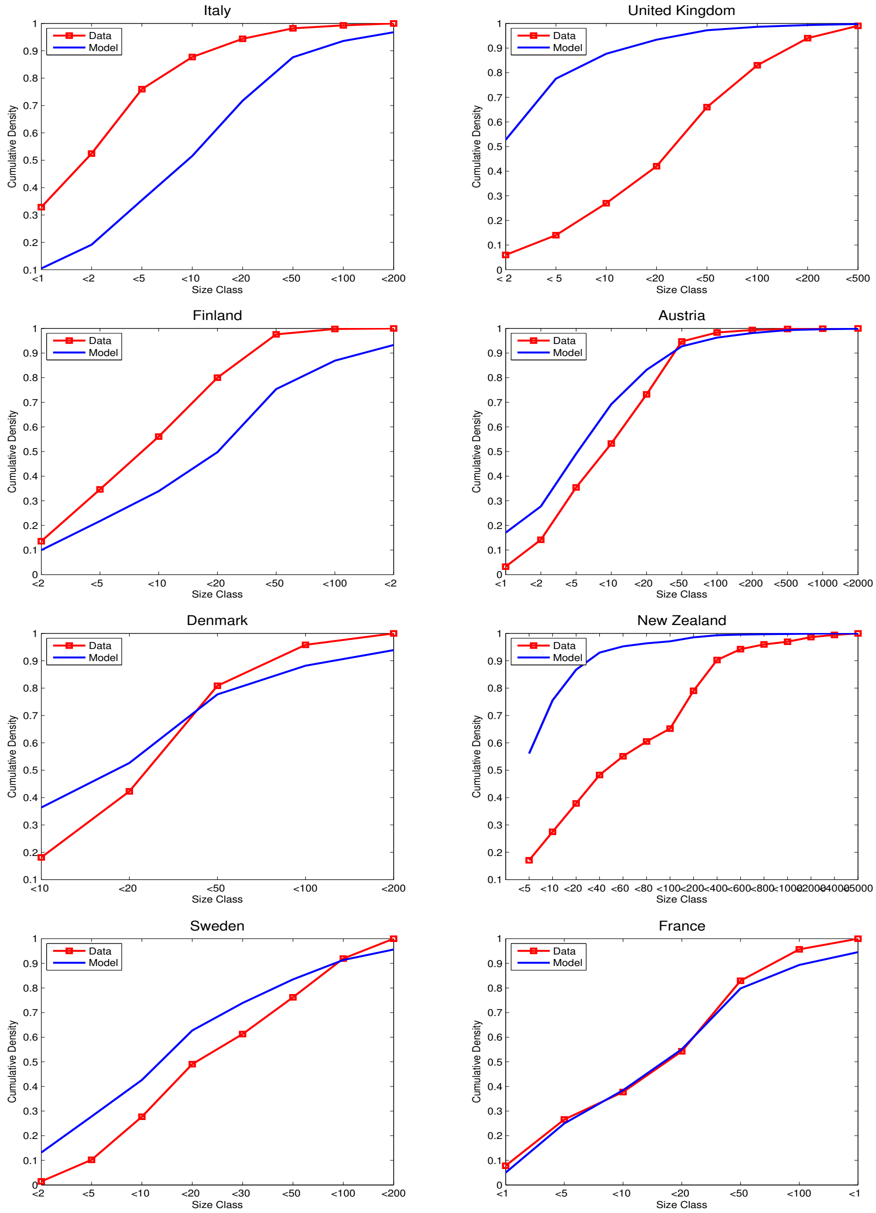
B.6 Model Predicted Farm Size Distribution (Q.2)



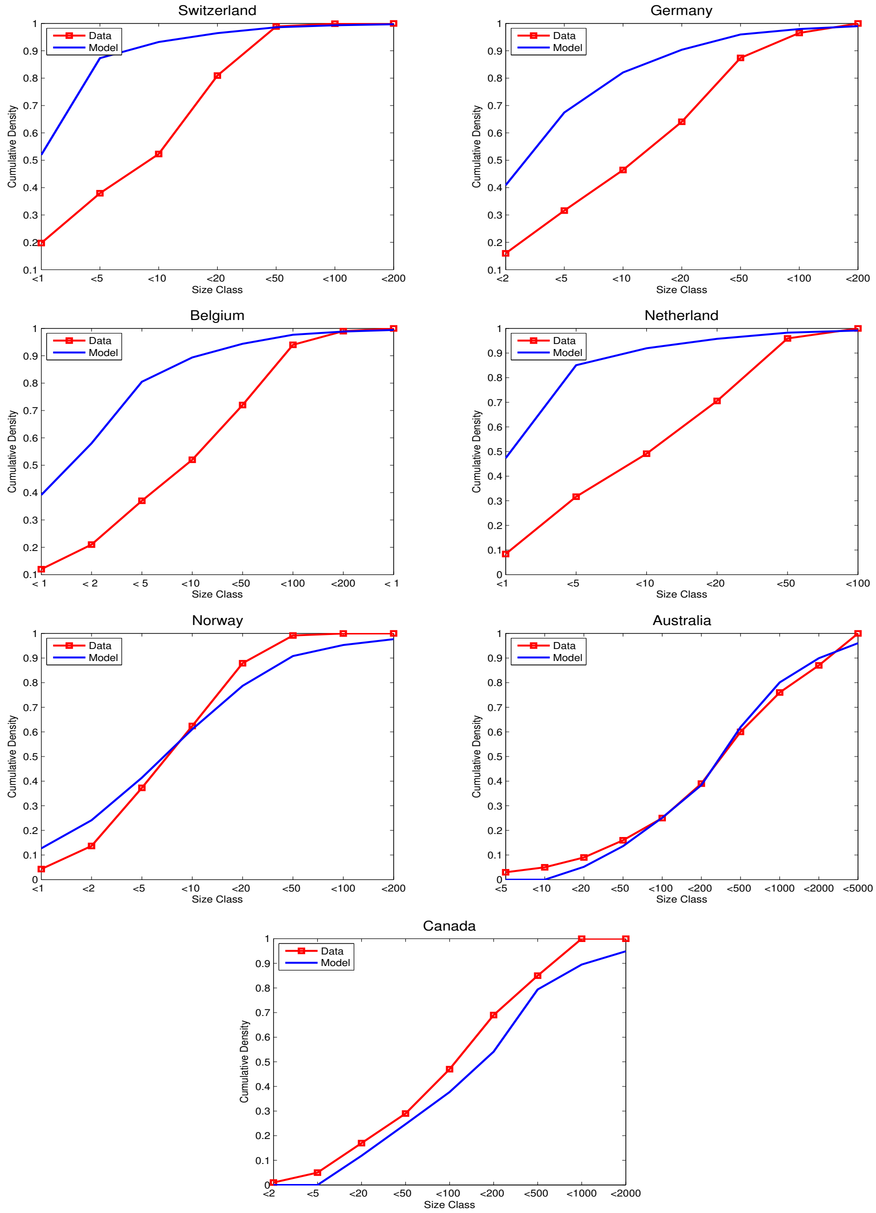
B.7 Model Predicted Farm Size Distribution (Q.3)



B.8 Model Predicted Farm Size Distribution (Q.4)



B.9 Model Predicted Farm Size Distribution (Q.5)



Code	rgdpwok	MFS (Ha)	No. Holding	Area (Ha)	Census Year
ARG	25715	468.97	378357	177437398	1988
AUS	46436	3,601.68	129540	466561000	1990
AUT	45822	26.42	273210	7217498	1990
BEL	50600	16.06	87180	1400364	1990
BFA	1824	2.79	886638	2472480	1993
BRA	18797	72.76	4859865	353611246	1996
CAN	45304	241.94	280043	67753700	1991
CHE	44152	11.65	108296	1262167	1990
CHL	23244	83.74	316492	26502363	1997
CIV	4966	3.89	1117667	4351663	2001
COL	12178	23.28	1547846	36033713	1988
DEU	42708	32.84	566900	18617900	1990
DNK	45147	34.14	81267	2774127	1989
DOM	12508	2.34	9026	21146	1995
ECU	12664	14.66	842882	12355831	1999
EGY	12670	0.95	3475502	3297281	1990
ESP	39033	18.79	2284944	42939208	1989
FIN	39611	61.88	199385	12338439	1990
FRA	45152	28.42	1006120	28595799	1988
GBR	40620	70.21	244205	17144777	1993
GRC	31329	4.50	802400	3609000	1995
HUN	21554	6.67	966916	6448000	1993
IND	9903	1.69	97155000	164562000	1985
IRL	47977	26.04	170578	4441755	1991
ITA	51060	7.51	3023344	22702356	1990
LKA	7699	0.81	1787370	1449342	2002
MAR	11987	5.84	1496349	8732223	1996
NIC	5697	31.34	199549	6254514	2001
NLD	45940	16.99	127367	2163472	1989
NOR	50275	9.97	99382	991077	1989
NZL	37566	223.43	70000	15640348	2000
PAK	6995	3.80	5071112	19252672	1990
PER	10240	20.15	1756141	35381809	1994
PRT	30086	6.74	594418	4005594	1989
SWE	40125	93.87	81410	7641890	1999
TUN	17753	11.58	471000	5455300	1994
UGA	1763	2.16	1704721	3683288	1991
URY	20772	288.31	54816	15803763	1990
USA	57259	186.95	2087759	390311617	1987
VEN	19905	60.02	500979	30071192	1997

Table 10: Summary Statistics of WCA