Skill Investment, Farm Size Distribution and Agricultural Productivity

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Abstract

This paper develops a general equilibrium model to quantitatively explain high labor share, low productivity and small farm size in agriculture in low income countries. The model features individual heterogeneity in skill that is augmentable over time and endogenous occupation choice. Calibrated to the U.S, the model can reproduce bulk of the observed variations in agriculture employment, agriculture output per worker and mean farm size across countries in the sample. In addition, the model generates endogenous farm size distributions that closely resemble the empirical counterpart for a large set of countries. Counterfactual exercises show TFP to be the main source of productivity differences.

JEL Classification: O11, O13, O41
Keywords: Income differences, agricultural productivity, Skill investment, farm size distribution.

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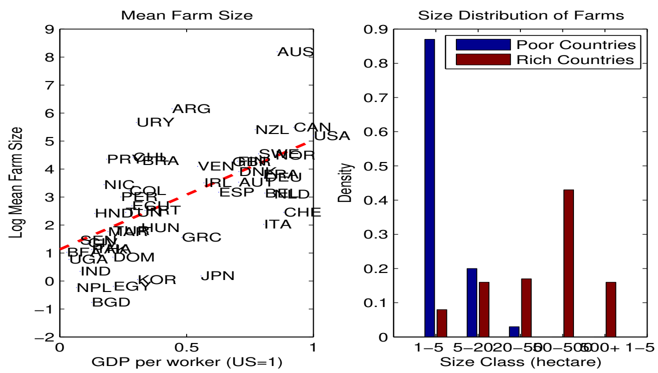
1 Introduction

Income and living standard vary substantially across countries. Understanding the origin of income differences have been the central question in economic development. While many studies have focus on productivity differences at the aggregate level, several recent studies have shown that productivity differences are asymmetric across different sectors (see Caselli [2005], Restuccia et al. [2008], Herrendorf and Valentinyi [2005], among others). Using PPP adjusted output measures, Restuccia et al. [2008] shows the poorest 10% countries from the world income distribution on average employs 85% of their labor in agriculture. On per-worker term, these countries only manage to produce less than 2% of the output produced in the richest 10% countries, where agriculture on average employs less than 5% of the labor force. In sharp contrast, outside the agriculture sector, the poorest 10% countries appear to be almost as productive as the richest 10% countries. Low living standard is thus characterized by high employment in an extremely unproductive traditional sector. The central economic development question is to ask why most people in poor countries work in a disproportionately unproductive sector? Understanding this question is important to understand aggregate income differences. A counterfactual calculation similar to the one in Caselli [2005] will illustrate this point succinctly. If all countries would have the U.S. agriculture productivity, and maintain their own labor allocation and nonagriculture productivity, cross-country income differences would almost disappear! A less ambitious experiment, where all countries have the U.S. relative productivity (agriculture/nonagriculture), while maintaining their own labor share and nonagriculture productivity, indicates that the income differences would shrink to a factor of 6, from a factor of 32, between the richest 10% and the poorest 10% countries.

Using data from World Census of Agriculture (WCA 1990, 2000), I document a new set of empirical observations regarding agriculture production across countries, namely, the scale of production positively correlates with levels of development. Here, scale of production is measured by the size of the plot[1]. Figure 1 (left) plots the logarithm of mean farm size (MFS) against real GDP per worker relative to the U.S. A clear positive trend emerges from the picture. As income rises, the mean farm size increases[2]. Moreover, in low income countries, agriculture production concentrates disproportionately in very small farms. Figure 1 (right) plots the size distribution for a set of representative countries. [3] In Ethiopia, 90% of the farms are less than 5 hectares. In contrast, 50% of the farms in the U.S. span over land that is 50 hectares or larger.



Source: GDP per worker: PWT 6.1; Mean farm size: author's calculation.

Figure 1: Size of Farms Across Levels of Development

Heterogeneity in farm size has important implications about productivity in agriculture. From 2007 U.S. Census of Agriculture, I compute the sales per worker and value added per worker[4] for farms of different size

[1]In WCA, the unit of observation is "holding", which by definition is "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. Single management may be exercised by an individual or household, jointly by two or more individuals or households, by a clan or tribe, or by a juridical person such as a corporation, cooperative or government agency".

[2]Larger size of a country does not necessarily imply higher MFS. Fox example, New Zealand is only about 1/40 as large as the U.S., yet its MFS is about 1.5 times that of the U.S..

[3]In the sample rich countries include U.S, Canada, UK and Australia. Poor countries include Uganda, Guinea, Ethiopia and Burkina Faso.

[4]Worker include both farm operator and hired worker

scales. The results are summarized in Figure 2. A typical farm in the largest scale class on average produce produce 16 times more output per worker than a typical farm in the smallest scale[5]. In value added terms, the productivity differences are even larger. Even though large farms tend to be more capital intensive, using reasonable factor shares, the productivity differences can not be fully explained by differences in capital stock across farms. Computed Solow residual is about 6-8 times higher in the largest farms, relative to the smallest ones. Data on productivity measures by size of a farm are not readily available for other countries, especially low income countries. However, several studies do find a similar relation between size and labor productivity for developing countries.Fan and Chan-Kang [2005] found a positive relationship between size and labor productivity for a set of asian countries. Byiringiroa and Reardon [1996] draw similar conclusion for farms in Rwanda.

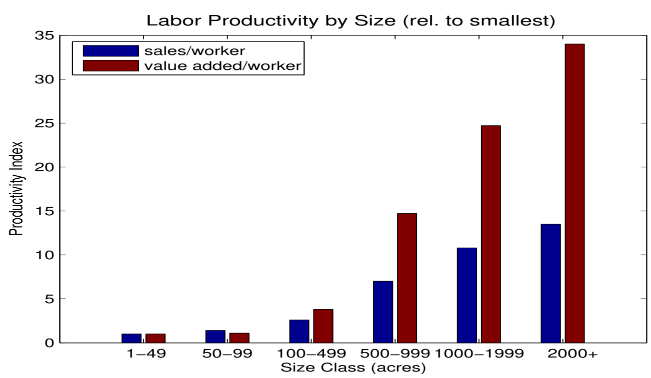


Figure 2: Productivity by Size of Farm (U.S)

How much of the productivity differences in agriculture can be explained by observed heterogeneity in scale of production, given the observed size-productivity regularity in the U.S. This is, of course, a valid development accounting question. To answer the question, I first estimate a log-linear function between productivity and mean farm size, and also between hired

[5]Similar results are obtained in earlier census (92, 97 and 02). Historical census also shows an increasing productivity gap between small and large farms. A 1000-acre farm appears no more productive than a 50-care farm in 1945.

labor and mean farm size, using U.S. census data. Taking the estimates as given, for each of the country I compute the implied productivity from the observed farm size distribution. Detailed calculations are given in appendix section 5.2. For a sample of 40 countries with complete data, the size heterogeneity along can explain about 30% of the variation in agriculture productivity across countries. Apparently, size differences are important to understand productivity differences. The natural development question is, of course, why farms are predominantly small in low income countries? A list of possible candidates can be tabulated, for example, barriers to capital for large scale of operation, institutional restriction on land acquisition and even geographical disadvantages. In this paper, I view the farm size heterogeneity as reflecting the skills of individual working in the agriculture sector. This idea traces back to Lucas' celebrated span of control model, where scale of production is tied to the skills of manager. This interpretation of cross-section size heterogeneity has support from U.S. data. U.S. Census of Agriculture reports the average size of holding of operators, whose primary occupation is farming. Interestingly, holding size exhibit substantial variation over operators of different age. Table 1 summarizes this pattern in 2007 census.

Age	25-34	35-44	45-54	55-64	65+
Mean Size	575	857	909	736	542

Table 1: Mean Holding Size by Age of Operator

The size profile exhibits a hump-shape, which is a well-known feature of life-cycle earning profile in income dynamics. Moreover, census data also indicates that younger operators spend more time off the farm than older operators. These observations suggest other factors, other than institutional restrictions and barriers, affect the average size of a farm. Moreover, these factors are most likely idiosyncratic and reflect characteristics of farm operators. An reasonable conjecture, in the same spirit of human capital accumulation, is that younger operators spend time augmenting their skills and hence expand their scale of operation overtime. The skill interpretation is thus consistent with the cross-section data on farm size across countries and across operators of different ages in the U.S.

The main contribution of this paper is to quantitatively explain agriculture labor share and productivity differences by appealing to differences in scale of production in agriculture. The model also generates endogenously farm size distributions that closely resemble empirical counterpart, and thus provides good discipline on model mechanism. The model features individual heterogeneity and endogenous occupation choices. Within the model, countries differ in their levels of aggregate, sector-neutral TFP. Individuals are heterogenous in initial skill type, and chooses occupation between worker and farm operator. Skill investment is incorporated into a version of Lucas' span-of-control model to endogenously generate s farm size distribution. In high TFP countries, wage rate is high and thus only high skill individuals will choose to operate a farm. As a result, farmers operate a larger farm and measured labor productivity is higher in these countries. The opposite is true in low TFP countries. The main mechanisms in the model are nonhomothetic preferences and skill accumulation. The former implies low income countries will have higher price of agriculture good, which renders farm operator a more attractive occupation. More people, even those with low skill, choose to work in the agriculture sector. The latter creates an additional avenue of productivity differences. The model is calibrated to reproduce some key moments and the observed size distribution of farms in the U.S. For a sample of 40 countries, the parameterized model is able to explain bulk of the cross-section labor allocations, sector productivity and farm size distributions.

Following the work by Hall and Jones [1999], many studies have been devoted to uncover the origin of income differences across countries. Using development accounting techniques, Chanda and Dalgaard [2008] show relative productivity across agriculture and nonagriculture sector are important determinant of aggregate productivity. Crdoba and Ripoll [2005] show that differences in human capital between rural and urban workers explain bulk of differences in aggregate productivity. Vollrath [2009] shows that misallocations of factors of production go far in explaining aggregate productivity differences. Looking at the agriculture sector only, Vollrath [2007] shows that inequality in land ownership is important to agriculture productivity, using an econometric model. This paper differs from the studies above in using a general equilibrium model. This paper is closely to related to a strand of literature that models explicitly an agriculture sector in a general equilibrium model. Restuccia et al. [2008] argue that distortion in intermediate inputs causes low agricultural productivity in developing countries. Gollin et al. [2004] argues low agriculture productivity in poor countries is due to unmeasured home production. These papers assume representative agents, while in this paper individual heterogeneity is important to productivity differences. This paper is closely related to Waugh and Lagakos [2009]. In their paper, low agriculture productivity is due to poor specialization. Facing subsistence, individual work in agriculture in which they do not have comparative advantage. This paper examines the scale of production in determining productivity differences, which their paper abstracts from. This paper is most closely related to a recent study by Restuccia and Adamopoulos [2009]. Both papers focus on scale of production in agriculture as an determinant of productivity, using a Lucas's span-of-control framework. However, this studies differs from theirs in two key dimensions. Firstly, this paper models explicitly occupation choices by heterogeneous individuals. Instead, they focus on the time allocation between sectoral production from a representative household's point of view. Secondly, this paper also explores the avenue of skill accumulation in determining the cross-country variation in farm size and agriculture productivity, which is abstracted from in their paper. I thus view this study as complementary to theirs. In the respect of modeling occupation choice using a framework of Lucas' span of control model, this paper is similar to Gollin [2007], who explores the secular decline in share of entrepreneur with rising income.

The paper is organized as follows. Section 2 presents the model. In section 3 I calibrate the model and discuss the results. Finally section 4 presents the conclusion remark.

2 Model

2.1 Environment

The economy is populated with a continuum of individuals who live for T periods. Size of each cohort is normalized to be 1. There is no lifetime uncertainty and no growth in population. Total mass of individuals in the economy at a point of time is T. When born, individuals obtain a draw of their skill type, denoted by z. Draws are *i.i.d* across individuals and over time. Each individual is endowed with one unit of physical time. Individuals have identical non-homothetic preferences as represented by the following utility function

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

(c_a, c_n) denote, respectively, agriculture consumption good and nonagriculture consumption good. η reflects the relative taste between two consumption goods. $\bar{a}$ is the subsistence level of agriculture consumption. $\bar{a} \geq 0$ implies a income elasticity of agriculture consumption less than unity. As a result, expenditure share in agriculture consumption declines with income level.

2.2 Technology

Nonagriculture output is produced with a simple linear technology

$$Y_n = A \cdot H_n$$

Here A is TFP level, and H_n is labor in the non-agriculture sector. Without loss of generality, I assume there is an representative nonagriculture firm in the economy.

Agriculture output is produced using a Cobb-Douglas technology

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

(H_a, L, z) denotes labor, land and skill, respectively. The technology exhibits constant return to scale at the aggregate level, but decreasing return to scale with respect to labor and land. The degree of "span-of-control", is summarized by parameter γ. Also note that TFP, A, enters both agriculture and nonagriculture technology, and thus is sector-neutral.

2.3 Skill Accumulation

Individuals can augment their skill according to

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

where $s_t \in [0, 1]$ is the fraction of time devoted to skill accumulation in period t. Skill accumulation requires time input only. While adding resources input can potentially strengthen model performance, I focus on time input for analytical simplicity. I also assume that skill does not depreciate over time. Individuals who spend s_t into skill accumulation, spend the remaining fraction $(1 - s_t)$ into market work in period t. As a result, there is a trade-off between current income and future income. A higher investment in skill reduces current income because less time is devoted into market, but increases the future ability and future income. Since skill is not fixed over time, throughout the paper, I will identify individuals by their *initial* skill draw. A type z individual refers to an individual whose initial draw of skill is z.

2.4 Individual's Problem

Individual, conditional on the initial draw of type, chooses an occupation to maximize discounted lifetime utility. Since there is no leisure and individuals take prices as given, this problem is equivalent to the one that maximizes discounted lifetime income. There are two occupations: worker and farm operator. Worker supply labor services in exchange of market wage rate. Farm operator hires labor and land from competitive market, in combination of their own skill, produce output and retain residual profit. Two assumptions are to be elaborated here. First, occupation choice is permanent and cannot be changed over one's life. For a stationary equilibrium, this assumption is harmless. Second, I assume that skill type is irrelevant for individuals who choose worker as occupation, i.e, all workers earn the same market wage rate regardless of their type. In equilibrium, this also implies that worker will not devote time into skill accumulation. As a result, the discounted lifetime income of a worker is simply

$$\sum_{t=1}^{T} w_t \cdot R_t^{1-t}$$

where w_t is the market wage rate at time t, and R_t is the return on saving from period t to $t+1$. By assumption, discounted lifetime income of workers is independent of their type.

Farm operator's problem is two-fold. Given (z_t, s_t), they choose amount of labor and land to hire as to maximize profit in period t. In addition, they also choose time investment $\{s_t\}_{t=1}^T$ to maximize discounted lifetime income. The optimization problem for a type $\tilde{z}$ farm operator can be written as

$$\begin{aligned} \max_{s_t} : \quad & \sum_{t=1}^{T} \pi(z_t(1-s_t)) \cdot R_t^{1-t} \\ s.t: \quad & z_{t+1} = z_t(1-\delta_t) + z_t \cdot s_t^{\theta} \\ & z_1 = \tilde{z}, \;\; s_t \in [0,1] \end{aligned}$$

Note that $z_t(1-s_t)$ is the measure of skills that an farm operator devotes to production. $\pi(z)$ is the maximized profit function that solves

$$\max_{x,h_a,\ell} : p \cdot A \cdot z^{1-\gamma} \left(h_a^{\alpha} \ell^{1-\alpha}\right) - w \cdot h_a - q \cdot \ell$$

where p is the price of agriculture output relative to nonagriculture output. Throughout the paper, nonagriculture output is used as numéraire.

2.5 Nonagriculture Firm's Optimization

Nonagriculture firm chooses labor to maximize profit

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

first order condition implies $w = A$, i.e., the market wage rate is equal to level of TFP.

There are competitive markets for labor and land, final consumption goods and intertemporal loans. As a result, I can solve the income maximization problem first, and then given maximized discounted lifetime income, solve for optimal consumption bundles. Next I define a stationary competitive equilibrium.

2.6 Equilibrium

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

To solve the model, I start with the income maximization problem. Given the skill investment technology, the following result can be established easily with the proof given in the appendix.

Lemma 1 *Time investment is independent of initial type*

Lemma 1 implies the slope of skill profile is the same for all operators, regardless of their type. In addition, time investment is decreasing with interest rate R. Let $\{s_t\}_{t=1}^{T}$ denote the sequence of time investments, then skill evolves according to $z_{t+1} = z_t(1+s_t^{\theta})$. It is convenient to define variable

x_t as follows

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

$\{x_t\}_{t=1}^{T}$ summarizes the level of skill at time t relative to when born for an operator. Note that since time investment is independent of initial type, $\{x_t\}$ is also independent of initial type. For a type z farm operator, the discounted lifetime income is given by

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

Since profit function $\pi(z)$ is strictly increasing in it argument, this implies the lifetime discounted income is strictly increasing in initial type z. The discounted lifetime income for a worker is simply $\sum_{t=1}^{T} w \cdot R^{1-t}$, which is independent of initial type. Clearly, there exists a cut-off type $\bar{z}$ such that individuals with initial type below $\bar{z}$ will choose worker as occupation. Individuals with initial type above $\bar{z}$ will operate a farm. The marginal individual, hence, must be indifferent between the two occupations. To solve for prices (p, q), I use indifference conditions for the marginal operator and land market clearing condition.

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

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

Equation (1) states that the marginal manager (type $\bar{z}$) is indifferent between worker and farm operator. Equation (2) states the demand of land from all operators must be equal to land endowment $\bar{L}$. Divide equation (1) by (2) yields an expression of land rental price

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

substitute into equation (1) yields relative price of agriculture 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 agriculture output is strictly decreasing in the cut-off type $\bar{z}$ and aggregate TFP. To compute the aggregate demand of consumption goods, I first compute the aggregate discounted income Y as given by

$$Y = (1 - G(\bar{z})) \cdot \sum_{t=1}^{T} w \cdot R^{1-t} + \int_{\bar{z}} Y_F(z) dG(z) + \bar{q} \cdot \bar{L} \sum_{t=1}^{T} R^{1-t} \tag{5}$$

Aggregate income is composed of wage income, residual profit and payment from land. Solving optimal consumption bundles and aggregating over individuals yields aggregate demand

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

$$C_n = \sum_{t=1}^{T} c_{nt} = \left[\sum_{t=1}^{T} (\beta R)^{t-1}\right] \cdot \left[\frac{Y - p \cdot \bar{a} \sum_{t=1}^{T} R^{1-t}}{\sum_{t=1}^{T} \beta^{t-1}}\right] \cdot (1-\eta) \tag{7}$$

The detail derivation of aggregate demand is given in appendix. Now turn to the supply side. Total measure of workers working in the agriculture sector is simply $H_a = \left[\sum_{t=1}^{T} x_t(1-s_t)\right] \cdot \int_{\bar{z}} h_a(z) dG(z)$. Total measure of worker is $T \cdot (1 - G(\bar{z}))$, so the aggregate output in the nonagriculture sector is

$$Y_n = A \cdot (T \cdot (1 - G(\bar{z})) - H_a)$$

Aggregate output in agriculture is given by

$$Y_a = \int_{\bar{z}} y_a(z) dG(z) \cdot \left[\sum_{t=1}^{T} x_t (1 - s_t) \right]$$

Good markets clearing conditions requires $C_a = Y_a, C_n = Y_n$. By Walras'law, loan market clears as well.

To illustrate the model mechanics, consider two economies: rich and poor, with TFP A_r and A_p respectively. In addition, assume that $A_r/A_p = g > 1$, i.e, rich economy have higher TFP. Holding land endowment fixed, the model predicts a lower cut-off type and a higher interest rate for the poor economy. To see this, lets assume the two economies will have the same cut-off type, and the same interest rate. 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 discounted income are proportional to aggregate TFP. Aggregate production of agriculture good is also proportional to TFP. However, with nonhomothetic preferences, demand of agriculture good drops by less than a factor of g in the poor economy. This is most clearly seen from equation (6), and thus there is excess demand in agriculture goods market. Relative price of agriculture good has to go up, and thus induces individual with lower type to become farm operators. The cut-off type is thus lower in the poor country. This also reduces the supply of nonagriculture good, so interest rate has to go up to clear the market. See Figure 3 for a pictorial illustration.

3 Calibration and Result

In this section, I parameterize the model. Model period is 10 years. Individuals are born at the age of 25, and die at the age of 75. Total population at a point of time is 5. TFP for the U.S is normalized to be 1. Assuming an annual discount rate of 0.96, I set $\beta = 0.96^{10}$. To estimate income share to operator and labor, I utilize the value added data published by USDA, which records the value added by various factors of production at the aggregate level. Detailed calculation are presented in appendix section 5.4. Over the period 1980-1999, the average share of income accruing to operators is 20%. I thus set $\gamma = 1 - 0.2 = 0.8$. This value is consistent with several existing estimates. Guner et al. [2008] estimates the span-of-control parameter to be 0.8 for the aggregate economy. A similar value is used inRestuccia and Rogerson [2008] for studying the effect of distortions on aggregate productivity in an economy with heterogeneous plants. For the manufacturing sector alone, Atkeson and Kehoe [2005] obtains an estimate of 0.85. The share of income accruing to labor averages about 5%. For land, the share is in a close neighborhood of 5%. I thus set $\alpha = 0.5$ to match the relative share of labor to land.

I restrict the initial type to be distributed 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 U.S. economy. I choose $\bar{a}$ to produce an agriculture employment share of 2% in the U.S. I choose η to generate a long run agriculture employment share of 0.5%. This corresponds to the asymptotic agriculture employment when subsistence consumption share of income is zero. Parameter θ determines the time allocation between skill investment and market work. I discipline θ using data on distribution of working days supplied by operators of different ages. Since time investment does not depend on initial type, operators of age i will supply the same amount time, $(1 - s_i)$, to farm work. Census of Agriculture reports the number of days *not* working in the farm for operators in 5 different age groups: 25-34, 35-44, 45-54, 55-64, 65+. Detailed calculations are given in appendix section 5.5. Using the these data, I compute the fraction of total working days supplied by operators from different age groups. Within the model, this statistic corresponds to $\frac{1-s_i}{\sum_{i=1} T 1-s_i}$, where s_i is the fraction of time devoted to skill investment for age i operator. In principle, I can choose θ to match any of the five moments. I choose θ to reproduce the share of operator aged 35-44. However, the implied shares for operators in other age groups are close to data as well, see Table 9 in appendix. Finally I choose $(\bar{L}, \mu, \sigma)$ to produce the observed size distribution of farms in the U.S. Parameter values are summarized in Table 8 in appendix. Figure 4 plots the calibrated size distribution against data. By construction, the model generated size distribution matches the data. In addition, as depicted in Figure 5 in appendix, the model also implies a land size distribution that fits data very well, even though it is not targeted. The model also generates a distribution of hired labor over size class that is qualitatively consistent with data [6], although it under-predicts the share of hired labor in small farms. One possible explanation is that elasticity of substitution between land and labor is less than unity, e.g., larger farms substitute capital with labor. With Cobb-Douglas technology, it is not surprising that the model under-predicts the share of hired labor in small farms.

3.1 Quantitative Experiment

In this section I test the model's ability to quantitatively predict the observed labor allocations and productivity differences across countries. The main data source is Restuccia et al. [2008]. Mean farm size is calculated from World Census of Agriculture (round 1990) published by Food and Agriculture Organization. The exercise proceeds as follows. All countries are identical except for their level of TFP (A) and land endowment ($\bar{L}$). In particular, they all face the same *ex-ante* distribution of skills types. Next I describe how I infer $(A, \bar{L})$ for each country. To compute TFP for country i, I exploit the linear technology in nonagriculture, which implies that TFP is the same as output per worker in the nonagriculture sector, the latter is directly available. Thus I compute TFP of country i, A_i, as follows

$$A_i = \frac{ynln_i}{ynln_{us}}$$

$$ynln_i = \text{Nonagriculture GDP per worker of country } i$$

[6] See Figure 6 in appendix. Three different shares are computed using raw head count, adjusted for working days, and using expenditure data, respectively.

Land endowment is approximated by land-employment ratio, which is directly available as well. Recall that I calibrated $\bar{L}$ for the U.S. to match size distribution of farms, I thus compute the land endowment for country i, $\bar{L}_i$, as follows

$$\bar{L}_i = \frac{ELR_i}{ELR_{us}} \cdot \bar{L}_{us}$$
$$ELR_i = \text{Employment-land ratio of country } i$$

The model, when fed with exogenous TFP and land endowments, predicts for each of the country the agriculture labor share (La), real output per labor in agriculture ($ryala$), real GDP per worker (rgdp) and mean farm size (mfs). Note that agriculture labor include both workers working in the agriculture sector and farm operators. Because relative price of agriculture output differs across countries, when computing GDP per worker I use U.S price as the international price. To facilitate comparison between model predictions and data, I divide countries in the sample into quintile by GDP per worker in the data. The sample consists of 40 countries. The results are summarized in Table 2.

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 2: Model vs Data, by Income Quintile

The model does well in predicting productivity differences. If we compare the bottom quintile against the top quintile, the differences in real agriculture productivity in the data is 25-fold, and the model predicts differences of the exact same magnitude. Between other low-middle income countries and the richest countries, the model predicts about 85% of the differences in agriculture productivity. Recall that between Q. 1 and Q.5 countries, the imputed differences in aggregate TFP are 5-fold, yet, the model magnify the differences in agriculture productivity into 25-fold. Several forces are at work. Nonhomothetic preferences implies higher equilibrium price of agriculture output in low TFP countries, and thus induces more people to become farm operators. Average skill, and hence productivity, is lower. In addition, the equilibrium interest rate is higher in low TFP countries, which depresses the incentive to accumulate skills. This further reduces the average skill and decreases productivity in low income countries. Since skill is positively correlated with scale of production, the model also generates increasing mean farm size with income level, as observed in the data. The model not only captures correctly secular rise of mean farm size with income level, but also predicts the entire *distribution* very well for individual country. See section 4.4 in appendix for model predicted farm size distribution of a set of countries. The ability of the model to capture the size distribution provides good discipline on the central hypothesis, namely, the productivity differences are driven by differences in skills.

The models's other quantitative predictions are also consistent with data. For the top quintile countries, the model correctly predicts the employment share in agriculture. For the bottom quintile countries, the model predicts a 48% agriculture employment share, which explains about 80% of the data. In general, model predicted agriculture employment is lower than the data counterpart. This reflects other forces at work other than aggregate TFP and land endowment. For example, high price of intermediate inputs, as discussed in Restuccia et al. [2008], induces farm operators to substitute labor for modern input and thus increases agriculture employment. This model also assumes a perfect labor market. However, in low income countries barriers to sectoral labor movements are common. For example, *Hukou* system in China imposes institutional restriction on immigration from rural villages to urban cities. Given a slight under-prediction of agriculture labor share, the model also under-predicts that differences in aggregate GDP per worker between the richest and poorest countries. For the rest of the countries in the sample, model predicted aggregate productivity are very close to data. Another aspect of the model that can be checked with data is the agriculture share of GDP. Using data from World Development Indicator, agriculture comprises a smaller share of total output as income rises. The model captures this correctly, although model generated agriculture shares of GDP are uniformly higher than the data counterpart for all countries. For the top quintile, the model predicts agriculture output comprises 10% of total output, while in the data it is 3%. For the bottom quintile, the model predicts the value to be 70%, while in the data is 30%. Lastly, the model also predicts the relative price of agriculture consumption to be higher in poor countries, which is consistent with existing studies (see, for example, Waugh and Lagakos [2009]).

3.2 Discussion

Overall the model, despite its simple structure, performs pretty well in reproducing the observed regularity in sectoral labor allocations and productivity across countries. Moreover, the model generates size distributions of farms that closely assembles their empirical counterpart for a large set of countries, which provides good disciplines on the avenue of skill heterogeneity as the sources of productivity differences in agriculture. The model also has some limitations. Firstly, calibrated share of land in agriculture production is 40%, which is a considerably large value. Griliches [1964] estimates the share to be around 16% for the U.S., though his estimates are for the period round 1950. In a more recent study, Restuccia et al. [2008] uses a similar share for land in a Cobb-Douglas technology. In addition, land endowment is approximated by land-employment ratio, and thus ignore possible differences in the quality of land. Another issue concerns the way TFP is inferred in the quantitative exercise. Linear technology provides an convenient way of linking aggregate TFP to nonagriculture output per worker. This approach assumes the frontier of the whole economy is well represented by the frontier of productions outside agriculture. Wile this assumption is reasonable for rich countries, it is problematic for less developed countries, where most of the productive activity takes place in the traditional sector. In addition, if viewed in the spirit of Waugh and Lagakos [2009], the inferred aggregate

TFP will be inflated for less developed countries because of self election. Only the most able people, in a comparative advantage sense, are working in the nonagriculture sector in low income countries. As a result, the measured productivity in nonagriculture sector is higher than the aggregate sector-neutral TFP.

The consensus in the literature establishes differences in TFP , rather than factors of production, being the main source of income differences. In the model, countries are different only in two dimensions: TFP and land endowment. Which one of these two exogenous variables are mainly responsible for the productivity differences? To answer the question, I perform a series of counterfactual experiments for a sample of low income countries[7]. Relative to the U.S, they have an inferred TFP 4.5 times smaller, and land endowment 2.1 times smaller. To disentangle the relative contribution, I change one exogenous variable at a time. Table 3 summarizes the results.

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 3: TFP versus Endowment (With Skill Accumulation)

The main finding conform with the current consensus. If the inferred TFP is maintained at the U.S. level, and land endowment is reduced by half, equilibrium labor allocation and productivity change minimally, relative to the U.S, though mean farm size drops by roughly a half. Differences in land endowment can't go far in explaining differences in labor allocation and productivity. In contrast, if those countries keep their own inferred TFP, there is a massive movement of labor into agriculture despite a higher land endowment. Moreover, agriculture productivity drops by a factor of 23, and mean farm size drops to 33 hectares. It is clear that TFP differences are much more important in shaping the observed labor allocation and productivity patterns. It is also interesting to note that the decomposition

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

of TFP and land endowment is not orthogonal. If both TFP and land endowment are changed simultaneously, the model predicts a 69% agriculture labor share and a 54-fold differences in productivity, almost the same as in the data. Again, this shows the ability of the model to quantitatively explain labor allocation and productivity differences across countries.

An important feature of the model is skill accumulation. First, skill accumulation is critical for the model to generate a size distribution that is well disciplined with the data. 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, using a dynamic version of Lucas' span-of-control model. 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. How much is skill accumulation contributing to the differences in labor allocation and productivity? To answer this question, I consider a variation of the model without skill accumulation, the environment is otherwise identical to the one described in section 2. Without skill accumulation, the problem is static. Individuals choose occupation, given skill type, that maximizes income. I calibrate the model to the U.S economy. However, as discussed before, without skill accumulation, it is impossible to calibrate the model to match the *entire size distribution* of farms. Instead, I choose type distribution parameters to target the first two moments of the size distribution. I choose preferences parameter to target current agriculture employment share and long run agriculture employment share. With the calibrated model without skill accumulation, I perform a similar counterfactual to see how much the model can explain the observed labor allocation and productivity differences between the set of poor countries and benchmark, which is U.S.. Specifically, I feed into the model a 4.5-fold differences in TFP and a 2.1-fold differences in land endowment, and compare model implications to data. Results are summarized in Table 4.

Without skill investment, the model performs less well in predicting the labor allocations and productivity differences. As in the case with skill investment, TFP differences are the main source of productivity differences.

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 4: TFP versus Endowment (No Skill Accumulation)

In the quantitative exercises, economies differ only in TFP and land endowment. This contrasts previous studies that explore distortions as the underlying sources of income differences. One important distortion is the distortion in intermediate inputs in agriculture production. From U.S agriculture census data, a large share (40%) of production expenses in agriculture are spent on intermediate inputs. In addition, Restuccia et al. [2008] document much higher price of intermediate inputs in less developed countries, and show that theses barriers to intermediate inputs are quantitatively important to agriculture productivity differences across countries. In this section, I explore the important of distortions in intermediate inputs within the model with skill heterogeneity. More specifically, I augment the agriculture technology to allow for intermediate input (X), i.e.,

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

Intermediate good X is produced in the nonagriculture sector. More specifically, one unit of nonagriculture output can either be consumed or converted into intermediate good at the rate of π. The resources constraint in the nonagriculture sector is given by

$$C_n + \pi \cdot X = Y_n$$

in equilibrium, π is the relative price of intermediate good to nonagriculture good. The economy is otherwise identical to the one described in section 2 except that I abstract from skill investment. The reason is to disentangle the effects coming from distortions from those stemming from skill investment. I calibrate the model to the U.S. I set $\gamma = 0.8$, and $\phi = 0.5$ to target the share of intermediate input in agriculture output. To target a land share of 16%, I let $\rho = 0.3$. For the U.S, price of intermediate π is normalized at unity. I then $(\eta, \bar{,}\mu, \sigma)$ to target a 2% current agriculture employment, 0.5% long run agriculture employment, 2% share of agriculture output of GDP, and the mean farm size. Within the sample, the poorest countries on average have 2.5 times higher price of intermediate inputs, compared to the U.S. As shown before, these countries also have 4.5 times lower inferred TFP and 2.1 times smaller land endowment. I perform counterfactual to evaluate the relative importance of each of these distortions. The results are summarized in Table 5

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 5: TFP versus Endowment (With Intermediate)

The main message from these counterfactuals is that distortions in intermediate inputs are important, especially when coupled with TFP, in shaping the labor allocations and agriculture productivity in less developed countries. While it seems to natural to extend the model to incorporate both intermediate input and skill accumulation, it is difficult to distinguish the relative contribution from these two components. As illustrated in the counterfactual, the decomposition is not orthogonal. While Restuccia et al. [2008] has shown convincingly that distortions in intermediate are essential to observed productivity differences, I focus on skill heterogeneity as an feasible explanation and view this study as complementary to their study.

4 Conclusion

This paper uses a simple general equilibrium model to quantitatively explain high labor share, low productivity and small farm size in agriculture sector of low income countries. I first document a set of facts regarding the scale of production in the agriculture sector across countries using data set from World Census of Agriculture published by Food and Agriculture Organization. Mean farm size positively correlates with income level. In addition, agriculture production concentrates mostly in small farms in poor countries. The main contribution of this paper is to interpret the observed farm size heterogeneity as reflecting the differences in skills of farm operators, using a version of Lucas' span-of-control model. This interpretation is supported by U.S data. Using U.S agriculture census data, I found the scale of production exhibits a hump-shape pattern over operator's life-cycle. Combined together, these cross-section data on farm size suggest skill differences are feasible explanation of differences in scale of production. Moreover, theses skills are potentially augmentable. In this sense, skill can be regarded as a form of human capital that is specific to agriculture production.

I develop a model that features individual heterogeneity in skills that are augmentable over time. Individuals are ex-ante identical, but ex-post different in terms of their occupation. Conditional on initial type, individual choose an occupation as well as skill investment to maximize discounted lifetime income. Equilibrium is characterized by a cut-off level of initial type such that individuals with initial type below the cut-off become worker, and individuals with initial type above the cut-off become farm operators. The level of cut-off type determines the measure of agriculture employment, as well as labor productivity. High income countries have a high cut-off and hence small agriculture employment and high labor productivity. Low income countries have low cut-off and hence large agriculture employment and low labor productivity. The model is calibrated to the U.S. to match some key moments as well as the size distribution of farms. Then I test the model's predictive ability for a sample of 48 countries. Countries have different aggregate sector-neutral TFP and land endowment, and are otherwise identical. The model predicts successfully the differences in agriculture productivity, and about 80% of the variation in labor allocation and productivity between richest and the poorest countries. The model also generates agriculture share of GDP and relative price of agriculture consumption that are consistent with data. In addition, for a large set of countries, the model generates an endogenous farm size distribution that closely assemble its empirical counterpart. A series of counterfactual within the model also conforms with the consensus in the economic development literature, namely, TFP differences, rather than differences in factors of production, are the main sources of income differences.

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5 Appendix

5.1 Proofs

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

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

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.

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

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

$$R^{1-t} = \lambda_t \theta s_t^{\theta - 1} \tag{8}$$

$$\lambda_t = R^{-t}(1 - s_{t+1}) + \lambda_{t+1}(1 - \delta_t + s_t^{\theta}) \tag{9}$$

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

$$\frac{\beta^t \eta}{c_{at} - \bar{a}} = \lambda \frac{p}{R^{t-1}} \tag{10}$$

$$\frac{\beta^t (1-\eta)}{c_{nt}} = \lambda \frac{1}{R^{t-1}} \tag{11}$$

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

$$\frac{p(c_{at} - \bar{a})}{c_n t} = \frac{\eta}{1-\eta}. \tag{12}$$

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

$$(c_{a,t+1} - \bar{a}) = \beta R(c_{at} - \bar{a}) \tag{13}$$

$$c_{n,t+1} = \beta R c_{nt} \tag{14}$$

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

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

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

5.2 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.

5.3 Occupation Choice Illustration

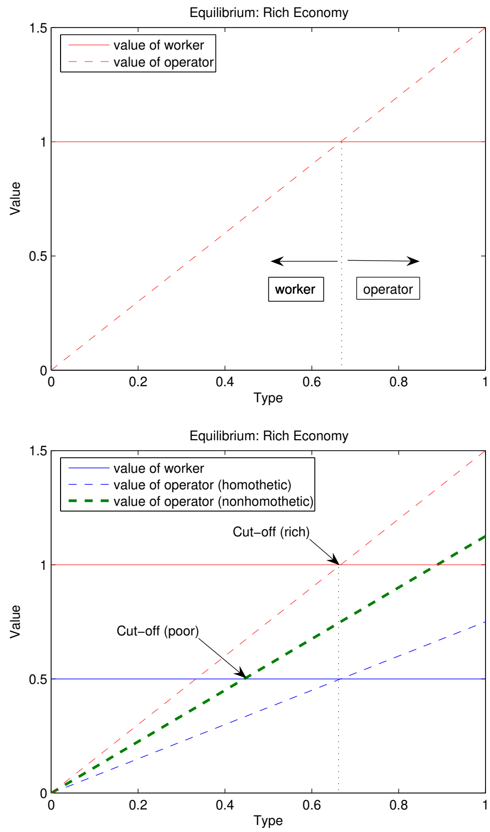


Figure 3: Illustration of Equilibrium Occupation Choice

5.4 Estimating Return to Scale Parameters in Agriculture

The main data sources is Value Added report published by USDA for the farming sector. The data set presents a detail account of farming production and expenses at the aggregate level. In principle, 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 the following factors of production: intermediate inputs, capital, labor, land and operators. In the data, these components corresponds to 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. I obtained aggregate level data for the U.S. from 1980-1999. The estimated income shares are summarized in the following table.

	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 6: Factor Shares in U.S. Farming

5.5 Working Days by Operator Age

From 1992 census of agriculture, I extract the number of days *not* working on the farm for farm operators by age. Table 7 summarizes the data.

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

	25-34	35-44	45-54	55-64	65+	Total
Days/Operator	94,932	178,809	183,206	236,016	344,159	1,037,122
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

Table 7: Days off Farm by Age of Operator

the share of days supplied by operators in age group i, denoted by s_i, 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. The implied shares are given below

Age	25-34	35-44	45-54	55-64	65+
Work Days (1000s)	17875	33908	34478	46589	66975
Share	0.09	0.17	0.17	0.23	0.34

5.6 Parameter Values

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

Table 8: Parameter Values

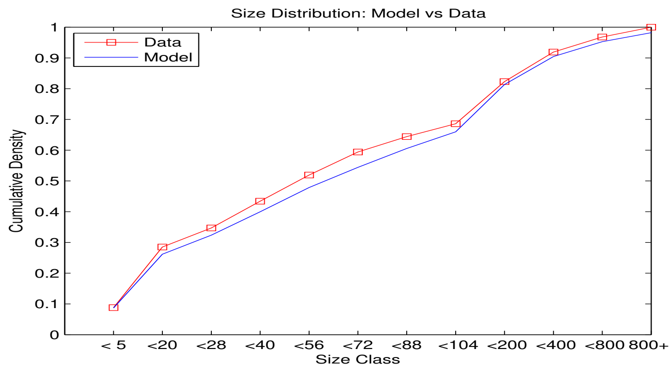


Figure 4: Calibrated Size Distribution

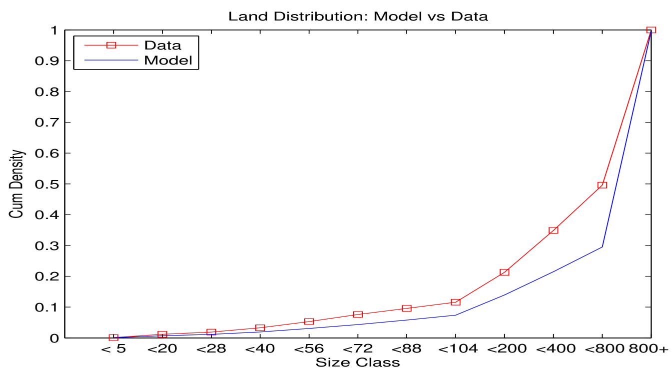


Figure 5: Implied Distribution of Land

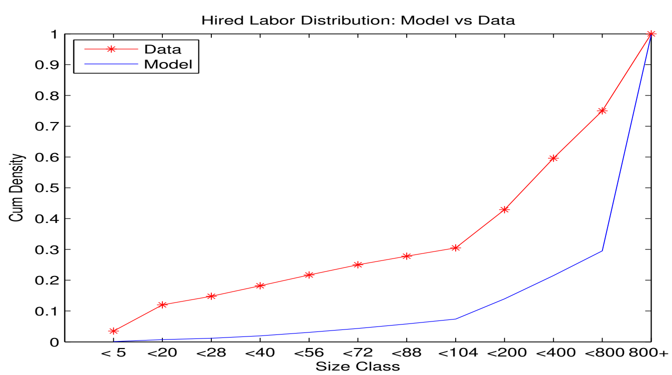


Figure 6: Implied Distribution of Hired Labor

Age	Data	Model
25-34	0.1	0.08
35-44	0.16	0.16
45-54	0.17	0.21
55-64	0.23	0.26
65+	0.34	0.29

Table 9: Time Share by Age of Operator

5.7 Model Performances

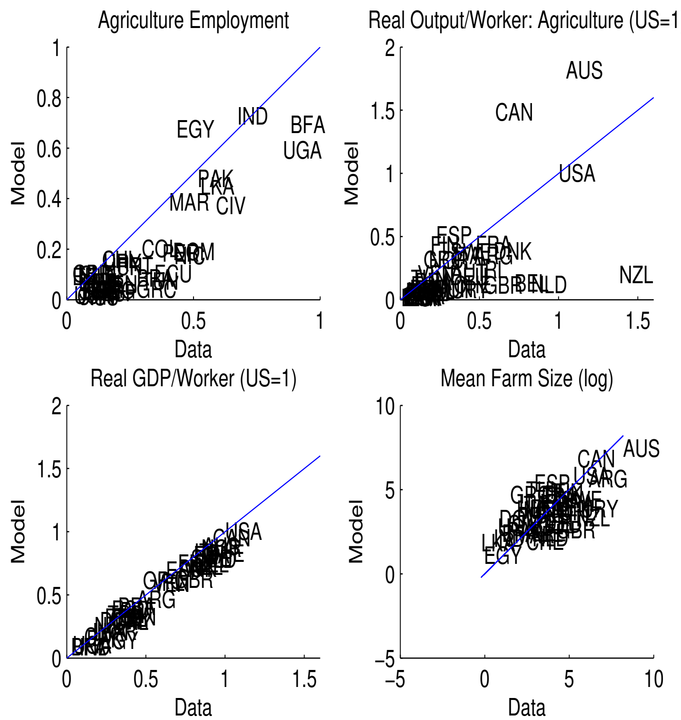
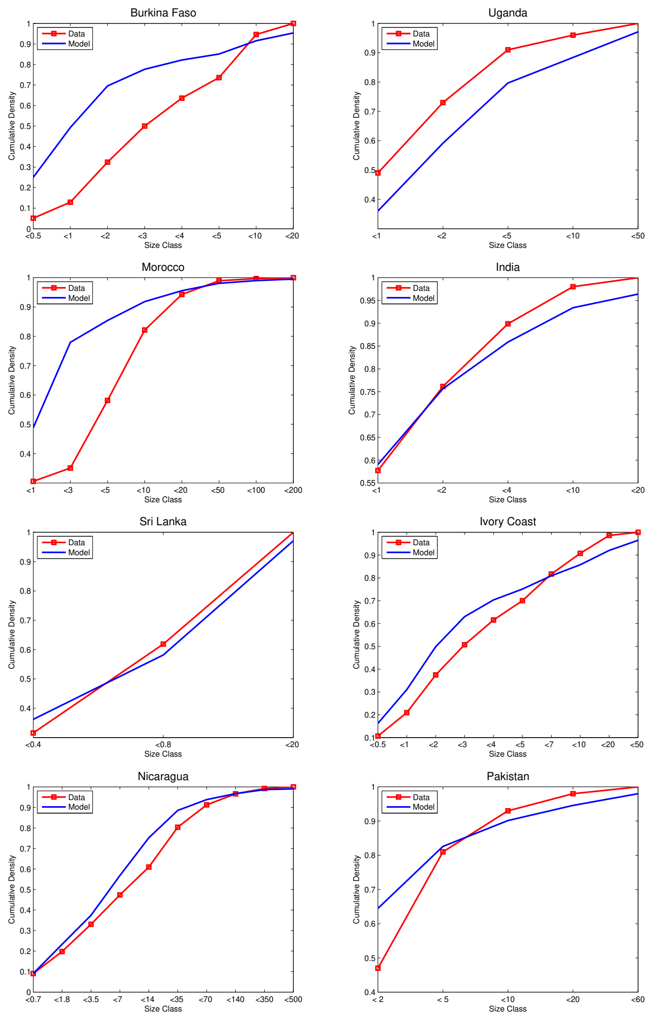
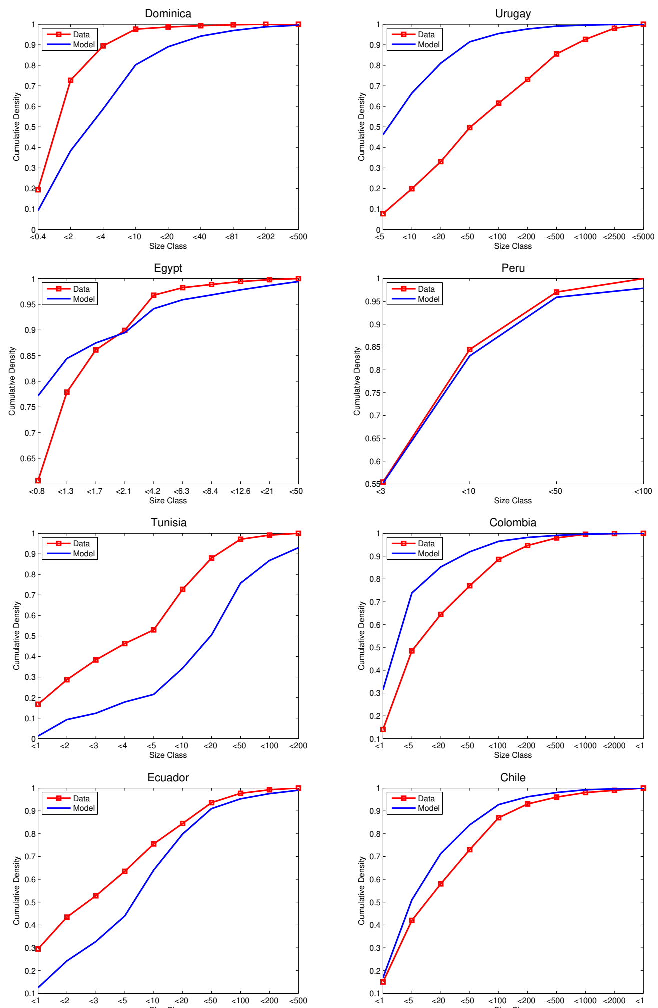


Figure 7: Model Prediction Against Data

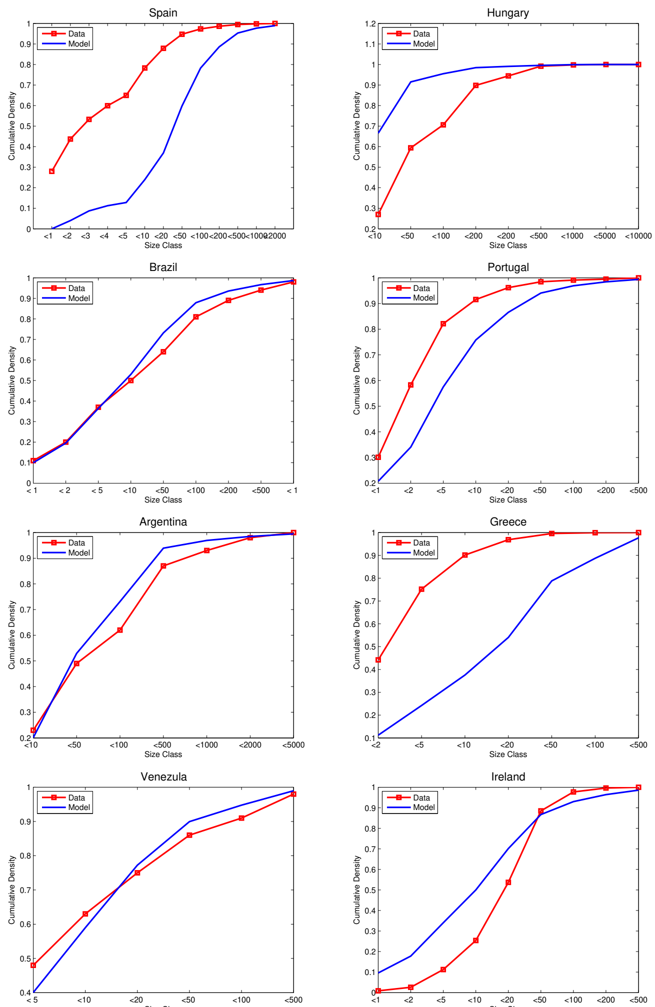
5.8 Model Predicted Farm Size Distribution (Q.1)



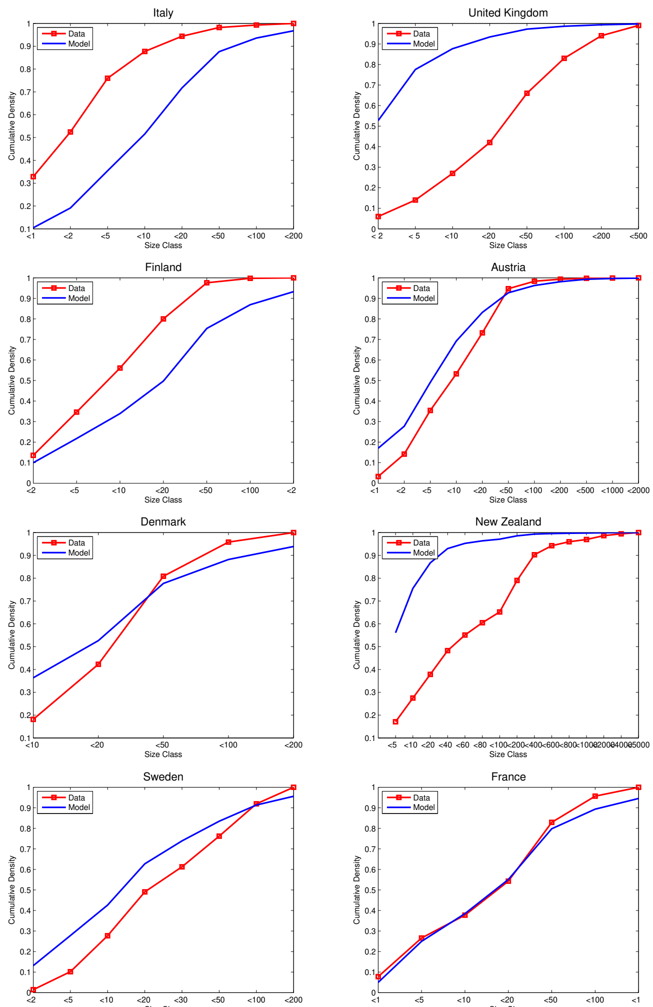
5.9 Model Predicted Farm Size Distribution (Q.2)



5.10 Model Predicted Farm Size Distribution (Q.3)



5.11 Model Predicted Farm Size Distribution (Q.4)



5.12 Model Predicted Farm Size Distribution (Q.5)