Skill Investment, Farm Size Distribution and Agricultural Productivity

Cai, Wenbiao

University of Iowa

9 January 2011

Skill Investment, Farm Size Distribution and Agricultural Productivity*

Wenbiao Cai †

University of Iowa

Abstract

Low labor productivity and small scale are key features of agriculture in poor nations. This paper assesses quantitatively the role of self selection and skill investment of farmers in accounting for these observations. I construct a two-sector overlapping generation model featuring individual heterogeneity in skill. Individuals self-select into farmers and workers as in Lucas (1978). As a key ingredient, I allow skill growth in response to optimal investment. The model is calibrated to reproduce the farm size distribution and other macroeconomic statistics in the US. Quantitative results show that low aggregate TFP and suboptimal skill investment are the main drivers of unproductive, small-scale agriculture in poor countries.

JEL Classification: O11, O13, O41

Keywords: Agricultural productivity, skill investment, farm size distribution, income differences.

1 Introduction

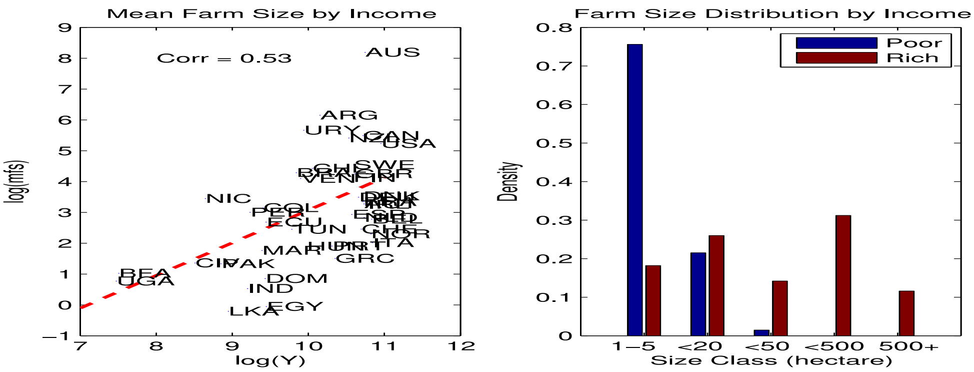
Two features of agricultural productions in poor nations are striking. The first one is its stunningly low productivity. Output per worker measured in international dollar is 60 times

*I thank B.Ravikumar for continuous encouragement and guidance, and participants in University of Iowa seminars for helpful comments. All errors are my own.

†Department of Economics, W210 John Pappajohn Business Building, Iowa City, IA 52242-1000. Email: wenbiao-cai@uiowa.edu.

lower in countries from the bottom 5% of the world income distribution, compared to that in the top 5%. The vast inequality in agricultural productivity across countries is well documented in Caselli (2005) and Restuccia *et al.* (2008)[1], and has simulated a large body of research providing feasible explanations. These explanations range from unmeasured home production as in Gollin *et al.* (2004), barriers to intermediate inputs as in Restuccia *et al.* (2008), low efficiency of workers as in Waugh & Lagakos (2010) and high transportation cost as in Adamopoulos (2006) and Gollin & Rogerson (2010).

The second, and relatively less well-known, feature is the small scale of production. I follow a long tradition in the literature and measure scale as the land size of a farm. International data on the size distribution of farms[2] are available from the World Census of Agriculture (WCA) published by the Food and Agriculture Organization (FAO) of the United Nations. The data set is an archive of national agriculture censuses from a wide range of developing and developed countries. FAO processes these national censuses and presents key summary statistics in a common, internationally comparable format.



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

Figure 1: Scale of Production in Agriculture Across Income Levels

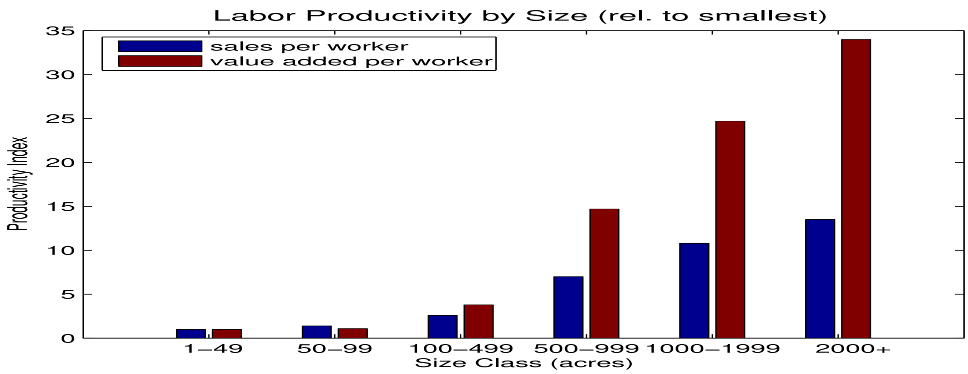
To demonstrate the enormous differences in scale of agricultural production across countries, I present two figures. On the left panel of Figure 1, I plot (log) mean farm size on the vertical axis, and (log) 1996 real GDP per worker on the horizonal axis. Mean farm size clearly rises with income per worker - with a correlation of 0.53. An average farm in the United States, for example, commands 180 hectares of land - 90 times the size of an average

[1]See also an early discussion in Kuznets (1959)

[2]The unit of observation in WCA is a holding - 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". Throughout this paper, I view a holding as identical to a farm.

farm in Uganda. The inequality in average farm size reflects the differences in the composition of farms. On the right panel of Figure 1, I plot the (average) farm size distribution from a group of low income countries, together with that from high income countries[3]. In poor nations, 73% of the farms are smaller than 5 hectares. In contrast, 50% of the farms in rich nations exceed 50 hectares in size. Most of the differences in mean farm size remain after controlling for country size and types of crops produced.

Farm level data from the US show that larger farms are remarkably more productive. Using 2007 agriculture census data, I find that farms in the top scale bracket are at least 16 times more productive in terms of sales per worker, and 30 times more productive in terms of value added per worker, compared to those in the bottom scale bracket[4]. Productivity also appears to increase monotonically with scale, as illustrated in Figure 2. Internationally, farm level productivity data as detailed as the ones in the US are not systematically available, especially for developing countries. In a study of 15 developing countries, Cornia (1985) found that larger farms have higher value added per worker, but lower value added per hectare[5]. With the US farm level productivity data, one can ask how much of the international productivity differences are due to differences in the size distribution of farms. I show that it can be as much as 1/3. Detailed calculations are given in Appendix B.



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

Figure 2: Productivity by Size of Farm

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

[4]Substantial differences remain when productivity is measured residually. Computed Solow residual ranges from 3 to 5 times higher for farms in top scale bracket. The results are also robust when earlier censuses (92, 97 and 02) are used.

[5]Similar findings are documented in Fan & Chan-Kang (2005) for a set of asian countries, and in Byiringiroa & Reardon (1996) for Rwanda. There is a also large literature debating the relation between farm size and *land* productivity. See Feder (1985) and reference therein.

Two questions naturally arise: why farms are predominantly small in poor nations and how deficiency in scale affects agricultural productivity in these economies. This paper attributes differences in scale and productivity to differences in unmeasured skill of farmers, and provides an unified explanation to these two questions.

Differences in efficiency of farmers arise from two distinct margins in the model. The extensive margin operates through self-selection. As in Lucas (1978), heterogenous individuals self-select into farmers and workers. The former produces agricultural output with an individual-specific technology, and the latter supplies labor for a wage. The extend of self-selection, or specialization as emphasized in Waugh & Lagakos (2010), determines the equilibrium pool of farmers. The intensive margin operates through on-the-job skill investment, which is the key ingredient of this paper. Cross-section data reveals on-the-job skill investment a critical component of farmer's productivity in the US. Table 4 records the time allocation between farm work and non-farm work by operators aged 25 and above, whose primary occupation is farming. Table 5 documents the life-cycle productivity profile of farm operators. The key observation is that young farmers allocate substantial amount of time to non-production activities that improve their productivity later on by as much as a factor of 1.5. This paper explores this margin in accounting for international productivity differences in agriculture.

I calibrate the model to the US. In particular, I ask the model to reproduce the size distribution of farms and time allocations of farmers. Ding so provides reasonable identification of the underlying skill distribution and imposes disciplines on the behavior of on-the-job skill investment. Given exogenous differences in aggregate efficiency and land endowment, the model is able to explain most of the differences in agricultural productivity and mean farm size across countries in the sample. Quite surprisingly, endogenously produced farm size distributions are remarkably close to the actual ones for a large set of countries, which I view as support of the mechanism stressed in this paper.

This paper is related to a large literature that studies cross country income differences, eg., Klenow & Rodriguez-Clare (1997), Prescott (1998), Hall & Jones (1999). The importance of dual economy in understanding aggregate income differences has been highlighted in several recent papers, e.g., Cordoba & Ripoll (2005), Chanda & Dalgaard (2008) and Vollrath (2009). In stressing the role of unmeasured skill, this paper is similar to Assuncao & Ghatakb (2003). However, they mainly focus on the negative correlation between size and *land* productivity in an analytical framework. After completing the paper, a recent paper by Restuccia & Adamopoulos (2009) was brought to my attention. Both papers focus on farm size heterogeneity across countries and use a version of Lucas (1978) to endogenously generate a size distribution. Two key features separate this paper from theirs. Firstly, they do not consider occupation choice, and instead focus on the uniform time allocation between farm and non-farm work across heterogenous household members. Gollin (2008) documents stark differences in the composition of labor force across levels of development. The implications from this paper is at least qualitatively consistent with his findings to the extent that most of the labor force in agriculture are own-account farmers. Secondly, this paper stresses the role of on-the-job skill investment by farmers, which is abstracted from in their study. Hence, I view this paper as complements to theirs.

The remaining of the paper is organized as follows. In section 2, I describe the economic environment and defines a competitive equilibrium. In section 3, I calibrate the model and present the quantitative results. Section 4 concludes.

2 Model

2.1 Environment

Each period a continuum of measure 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, $z \in \Re^+$, 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. $\bar{a}$ is typically interpreted as subsistence consumption level. $\bar{a} > 0$ implies an income elasticity of agricultural consumption less than unity, which is a standard feature in models of structure change.

Each member is endowed with one unit of physical time. Households equally own the stock of land $\bar{L}$. There is no population growth or lifetime uncertainty. Total measure of individuals at any point in time is T.

2.2 Technology and Household Decision

Everyone works in this economy and faces two occupations: farm manager and worker. All workers, regardless of skill type, earn the same wage rate. A farm manager 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 in competitive markets at price p. All prices are expressed relative to the price of nonagricultural output. A farm manager solves

$$\max_{\{h_a, \ell\}} \quad p \cdot Y_a - w \cdot h_a - q \cdot \ell$$

The residual profit, $\pi(z)$ is retained by the farm manager. It is straightforward to show that

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

Although the initial realization is drawn exogenously, skill can subsequently grow through investment. The law of motion is given by

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

where $s_t \in [0, 1]$ is time input. Each period, the household head considers tow alternative uses of each member's time: market work or skill investment. If s_t fraction is allocated to skill improvement, then $(1 - s_t)$ is supplied to market work. This skill technology assumes time as the sole input, and hence abstracts from resources 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.

When born, the household head chooses occupation, sequences of skill investment, and sequence of consumption and saving to maximize discounted household utility. For simplicity, I assume that occupation can not change over time. This assumption is not restrictive because I focus on the steady state in the quantitative analysis. For the same reason, I state the household maximization problem from an arbitrary cohort as follows

$$\max_{\{c_{at}, c_{nt}, s_t\}} : \sum_{t=1}^{T} \beta^t U(c_{at}, c_{nt})$$
$$s.t: \sum_{t=1}^{T} \frac{pc_{at} + c_{nt}}{R^{1-t}} \leq Y$$

where R denotes the return on savings, and Y denotes the *maximized* discounted income of the household. The following lemmas establish results that characterize the stationary equilibrium, where all prices are constant.

Lemma 1 *Workers don't invest in skill improvement.*

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, Inada conditions ensure skill investment profitable for all farm managers. The following lemma characterizes the optimal investment profile of farm managers.

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 managers, 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 the initial draw. Clearly, $\{x_t\}$ is independent of skill type. This allows a simple expression of lifetime discounted income of a type z farm manager

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

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 managers.*

The most able members will manage 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 manager, whose skill type is $\bar{z}$, is indifferent between two occupations. The maximized discounted income of a 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 Nonagricultural 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 represents economy-wide efficiency. 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 manager's profit maximization, and H_n solve nonagricultural firm's profit maximization; (3) prices are competitive; (4) all markets clear.

To solve the model, I begin by solving for prices (p, q). Equation (1) below states the indifference condition of the marginal manager. 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 for 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 aggregate TFP. To the extend that poor countries also have lower TFP, this implies higher price of agricultural consumption in low income countries. Solving for optimal consumption bundles and aggregating over generations yields the aggregate demand of two consumption goods

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

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

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 obtained by first integrating over farm managers within a household, and then summing over generations

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

Similarly, aggregate agricultural output is given by

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

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 $Y_n = A \cdot H_n$. Good markets clearing conditions requires $C_a = Y_a, C_n = Y_n$. Loan market clears by Walras' law.

Lemma 4 *Low TFP economy has a lower cut-off skill level, and a higher interest rate.*

The proof is given in Appendix B. Low aggregate TFP adversely impacts the quality of farm managers through both the extensive margin and the intensive margin. On one hand, low TFP induces a larger pool of farm managers at the cost of lower average efficiency. The reason is that, with a lower cut-off skill level, the marginal manager is of lower quality. On the other hand, higher interest rate in low TFP economy also reduces the incentive to invest in skill improvement because future income gets discounted more. As a result, the skill profile is less steep. Both margins lead to lower average skill of farm managers, which translates into low measured labor productivity and small scale.

3 Quantitative Analysis

3.1 Calibration

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 US is normalized to be 1. Parameters of the agricultural production function are directly inferred from agriculture value added data in the US (see Appendix A). Over the period 1980-1999, the average share of agricultural output accruing to farm operators is 20%. I thus set $\gamma = 1 - 0.2 = 0.8$. This paper is certainly not the first one to estimate the span-of-control parameter. However, existing works either focus on the aggregate economy as in Guner *et al.* (2008), Restuccia & Rogerson (2008) and Gollin (2008) or the manufacturing sector as in Atkeson & Kehoe (2005). The value of the span-of-control parameters from these studies range from 0.8 to 0.9. A value of 0.8 for the agricultural sector appears compatible with these estimates[6]. Over the same period, return to land and hired labor are almost identical, which suggests $\alpha = 0.5$ 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 US economy in 1992. From the 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

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

allocations of farm operators. From 1992 census of agriculture, I extract 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. 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 managing a farm. 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[7]. Finally, I ask the model to reproduce the observed size distribution of farms in the US. Figure 3 plots the calibrated size distribution against data. In addition, as depicted in Figure 4, the model also implies a land distribution that fits the data very well, even though it is not targeted. These figures are presented in Appendix B.

3.2 Quantitative Results

In this section I assess the model's ability to quantitatively explain cross-country variations in agricultural productivity and scale of production. Data on sectoral productivity, sectoral labor shares and land endowment are from Restuccia et al. (2008). The size distributions of farms are constructed 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 administered independently in each member country - possibly in different years (see Table 10 for country specific census years). In principle, this study should be restricted to countries with their censuses conducted in 1985. As a first pass, however, I merge these two data sets with two defenses. First, census of agriculture typically takes place every 5 years in most countries, if at all. 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. It is unlikely that the composition of farms will undergo drastic changes over a period of five years.

Countries differ in their aggregate efficiency (A) and land endowment ($\bar{L}$), and are otherwise identical. In particular, they all face the same *ex-ante* distribution of skill types. I

[7]See Appendix B for details.

infer A_i and $\bar{L}_i$ of country i 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 is the sum of agricultural workers and farm managers. When computing aggregate output, US price is used as international price to make results comparable to the data, which is PPP adjusted. To facilitate comparison between model and data, I divide countries in the sample into quintile by real 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[8]. The results are summarized in 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. Note that nonagricultural output per worker differs by at most a factor of 5 between Q.1 countries and Q.5 countries. Hence exogenous differences in aggregate efficiency account for about 50% of the differences in agricultural productivity. The differences in idiosyncratic productivity of farmers explain the remaining half. These results suggest that the quality of farmers are at least as important as overall

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

efficiency for understanding productivity differences in agriculture.

Farms in rich nations are much larger compared to those in poor nations in the data, and so are they in the model. The last two columns of Table 1 records the mean farm size in each quintile. The model also has rich predictions about the entire *farm size distribution* across countries. In Appendix B I plot the endogenously generated 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 vast variations across levels of income. For a large set of countries the model can reproduce the actual distributions almost exactly, which I view as a success of the model.

Agriculture, despite its low productivity, absorbs most of the labor force in poor nations. The model also predicts a much higher agricultural labor share in poor economies. For the bottom quintile countries, the model predicts a 48% agricultural employment share - about 80% of the actual share. The fact that the model fails to generate a larger agricultural labor share suggests other forces at work that are not specifically modeled here. Among other things, barriers to sectoral labor movements are particularly important to the question posted here. Moreover, such barriers are prevalent in developing nations as evidenced by substantial disparities in rural-urban earnings. One famous example is the *Hukou* system in China that imposes institutional restrictions on immigration from rural villages to urban cities. Unfortunately, direct measures of barrier to labor movement are not available, making further quantitative analysis that incorporates these barriers infeasible [9].

Agriculture's share of total output declines as income rises - a macroeconomic implication of Engel's Law. The model predicts agricultural output to be 10% of the aggregate output in the top quintile countries, and 70% in the bottom quintile countries. In the data, the value is 3% and 30%, respectively. One possible explanation is that the model over-predicts the relative price of agricultural output, resulting in a higher agriculture share of GDP when measured at domestic prices. Using ICP data from the World Bank, I compute the relative price between "agricultural consumption" and "nonagricultural consumption" for all available countries[10]. The relative price in 2005 is around 4 times higher in the 10th percentile country, compared to the 90th percentile country. In the model, this relative price

[9] Some measures are constructed indirectly using first order conditions in Restuccia et al. (2008). A straightforward incorporation of these barriers improves model's prediction substantially. However, the fact the farm managers and workers are treated differently in my model complicates the mapping between my model and the data. As a result, I do not pursue this route.

[10] "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)

ratio is 2.8, which is roughly in line with the data.

Consensus in the development literature attributes TFP differences as the main source of income differences. The poorest countries in the sample[11] have 4.5 times lower TFP and 2.1 times lower land endowment, relative to the US. If TFP of these countries is fixed at the US level, and land endowment at its country-specific value, equilibrium allocations change minimally. Poor endowment is the least to blame for low agricultural productivity. In contrast, if TFP is fixed at its country-specific level, and land endowment at the US level, there is a 22-fold reduction in agricultural productivity. Table 2 summarizes these results. A reversed calculation implies that improvement in overall efficiency benefits agriculture disproportionately, i.e., a 4.5-fold improvement in overall efficiency increases agricultural productivity by a factor of 22. Public policies, albeit agriculture oriented, should aim at improving overall efficiency through better institutes, better educations and more efficient markets.

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

3.3 Discussion

An novel and key feature of the model is to embed skill accumulation in an otherwise standard Lucas' span-of-control model. A similar idea was explored 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 highlight 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 US. Moreover, given exogenous variables, the model without skill accumulation in general explains less of the cross-section differences in labor

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

allocation and productivity. Details of calibration and quantitative results are presented in Appendix B.

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

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

Intermediate good can be converted from nonagricultural output at the rate of π. For expositional purposes, I suppress skill accumulation. Detailed calibration and results are given in Appendix B. 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).

Restuccia et al. (2008) explore the impact of intermediate input on agricultural productivity through the *intensive margin*. However, there are evidences suggesting that the *extensive margin* might also be important. Evenson & Gollin (2003) document a substantial lag in adoption of modern variety in Sub-Saharan Africa during the 1960s and 1970s. There are two ways skill might affect the use of modern inputs. Through the extensive margin, low skill might impede the farmer's learning of the new variety, and delays the decision of adoption. Through intensive margin, low skill farmers might use modern variety to a less extent if skill is complementary to modern varieties. Quantitative explorations from these angles are left for future work.

4 Conclusion

In this paper I develop a model that links scale of production and productivity to unmeasured skills of farmers. In poor countries, subsistence need and low wage rate render farming a better option for even low skill individuals. On one hand, self-selection results in a larger pool of farm managers at the cost of lower average efficiency. On the other hand, sub-optimal investment on the job further depresses skill growth. The calibrated model can explain most of the differences in agricultural productivity between the 80th percentile country and 20th percentile country. The results also suggest that quality of farmers is at least as important as TFP in accounting for cross-country differences in agricultural productivity. Moreover, the model is able to capture not only the differences in the mean farm size, but also the variation in the *size distribution* across countries.

The agricultural sector characterized in this paper is "poor but efficient", as articulated in Schultz (1964). Nonetheless, various distortions geared specifically towards agriculture are also important. Distortions such as barriers to sectoral labor movements, and implicit government taxation on agriculture as discussed in Krueger *et al.* (1988) and Anderson (2009), might be key to understand the coexistence of a large labor force and low productivity in agriculture in poor nations. While eliminating these distortions is important for development in agriculture, public policies favoring better institutions, faster technology adoptions and more efficient markets are of first order importance in improving overall living standards.

References

Adamopoulos, Tasso. 2006. Transportation Costs, Agricultural Productivity and Cross-Country Income Differences. *Working paper.*

Anderson, Kym. 2009. *Distortions to Agricultural Incentives: A Global Perspective, 1955-2007.* The World Bank and Palgrave Macmillan.

Assuncao, Juliano J., & Ghatakb, Maitreesh. 2003. Can Unobserved Heterogeneity in Farmer Ability Explain the Inverse Relationship between Farm Size and Productivity. *Economic Letters*, **80**(2), 189–194.

Atkeson, Andrew, & Kehoe, Patrick J. 2005. Modeling and Measuring Organization Capital. *The Journal of Political Economics*, **113**(5), 1431–1475.

Bhattacharya, Dhritiman. 2009. Aggregate Barriers, Eestablishment Size and Economic Development. *Job market paper.*

Byiringiroa, Fidele, & Reardon, Thomas. 1996. Farm Productivity in Rwanda: Effects of Farm Size, Erosion, and Soil Conservation Investments. *Agricultural Economics*, **15**(2), 127–136.

Caselli, Francesco. 2005. Accounting For Cross Country Income Differences. *In:* Aghion, Philip, & Durlauf, Seteven D. (eds), *Handbook of Economic Growth.* ELSEVIER.

Chanda, Areendam, & Dalgaard, Carl-Johan. 2008. Dual Economies and International Total Factor Productivity Differences: Channelling the Impact from Institutions, Trade, and Geography. *Economica*, **75**(300), 629–661.

Cordoba, Juan Carlos, & Ripoll, Marla. 2005. Agriculture, Aggregation, and Cross-Country Income Differences. *Working paper*.

Cornia, Giovanni Andrea. 1985. Farm size, land yields and the agricultural production function: An analysis for fifteen developing countries. *World Development*, **13**(4), 513–534.

Evenson, Robert E., & Gollin, Douglas. 2003. Assessing the Impact of the Green Revolution, 1960-2000. *Science*, **300**(5672), 758–762.

Fan, Shenggen, & Chan-Kang, Connie. 2005. Is Small Beautiful? Farm Size, Productivity, and Poverty in Asian Agriculture. *Agricultural Economics*, **32**, 135–146.

Feder, Gershon. 1985. The Relation Between Farm Size and Farm Productivity : The Role of Family Labor, Supervision and Credit Constraints. *Journal of Development Economics*, **18**(2-3), 297–313.

Gollin, Douglas. 2008. Nobody's Business but My Own: Self-employment and Small Enterprise in Economic Development. *Journal of Monetary Economics*, **55**, 219–233.

Gollin, Douglas, & Rogerson, Richard. 2010. Agriculture, Roads, and Economic Development in Uganda. *Working paper*.

Gollin, Douglas, Parente, Stephen L., & Rogerson, Richard. 2004. Farm work, Home Work and International Productivity Differences. *Review of Ecconomic Dynamics*, **7**(4), 827–850.

Guner, Nezih, Ventura, Gustavo, & Yi, Xu. 2008. Macroeconomic Implications of Size-Dependent Policies. *Review of Economic Dynamics*, **11**, 721–744.

Hall, Robert E., & Jones, Charles I. 1999. Why Some Countries Produces So Much More Output per Worker Than Others. *The Quaterly Journal of Economics*, **114**(1), 83–116.

Klenow, Peter, & Rodriguez-Clare, Andres. 1997. The Neoclassical Revival in Growth Economics: Has It Gone Too Far? *Pages 73–114 of:* Bernanke, B., & Rotemberg, J. (eds), *NBER Macroeconomics Annual 1997*, vol. 12. MIT Press.

KRUEGER, ANNE O., SCHIFF, MAURICE, & VALDS, ALBERTO. 1988. Agricultural Incentives in Developing Countries: Measuring the Effect of Sectoral and Economywide Policies. *World Bank Economic Review*, **2**(3), 255–271.

KUZNETS, SIMON. 1959. *Six Lectures on Economic Growth.* New York: Free Press.

LUCAS, ROBERT E. 1978. On the Size Distribution of Business Firms. *Bell Journal of Economics*, **9**(2), 508–523.

PRESCOTT, EDWARD C. 1998. Needed: A Theory of TFP. *International Economic Review*, **39**(3), 525–51.

RESTUCCIA, DIEGO, & ADAMOPOULOS, TASSO. 2009. The Size Distribution of Farms and International Productivity Differences. *Draft.*

RESTUCCIA, DIEGO, & ROGERSON, RICHARD. 2008. Policy Distortions and Aggregate Productivity with Heterogeneous Plants. *Review of Economic Dynamics*, **11**(4), 702–720.

RESTUCCIA, DIEGO, YANG, DENIS TAO, & ZHU, XIAODONG. 2008. Agriculture and Aggregate Productivity: A Quantitative Cross-country Analysis. *Journal of Moneytary Economics*, **55**(2), 234–250.

SCHULTZ, THEODORE W. 1964. *Transforming Traditional Agriculture.* New Haven: Yale University Press.

VOLLRATH, DIETRICH. 2009. How Important are Dual Economy Effects for Aggregate Productivity? *Journal of Development Economics*, **88**(2), 325–334.

WAUGH, MICHAEL E., & LAGAKOS, DAVID. 2010. Specialization, Agriculture, and Aggregate Productivity Differences. *Working paper.*

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-country/en/
- **World Development Indicator:** http://data.worldbank.org/indicator
- **Factor Shares in U.S Farming:** Data are from National Agriculture Statistics Services administrated by the Department of Agriculture, and can be accessed through http://www.ers.usda.gov/Data/FarmIncome/FinfidmuXls.htm. In the calculation, government transfers are subtracted from total output and real estate and non real estate interest are included as capital income.

	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
Managers	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 *off* the farm for farm operators by age (Panel A), assuming 250 working days a year. Midpoint of the interval is used as the interval average.

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 2:
Profit function is linear in skill, i.e.,

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

In a stationary equilibrium, the optimal sequence of skill investment is the solution to the following problem

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

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 4:
Consider two economies with $A_r = g \cdot A_p$ with $g > 1$, and assume the threshold level of skill and interest rate are the same. Equation (3) implies $q_r = g \cdot q_p$. 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, Equation (5) suggests that demand of agricultural consumption drops by less than a factor of g. Excess demand pushes up the price of agricultural consumption, and reduces the threshold level of skill in low efficiency economy. This implies a higher labor share in agriculture, and a decline in the supply of nonagricultural good. Interest rate must rise to offset the excess demand.

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

$$
\begin{aligned}
log\left((y/h)_i\right) &= b1 + b2 \cdot log(s_i) \\
log\left((hl)_i\right) &= c1 + c2 \cdot log(s_i)
\end{aligned}
$$

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

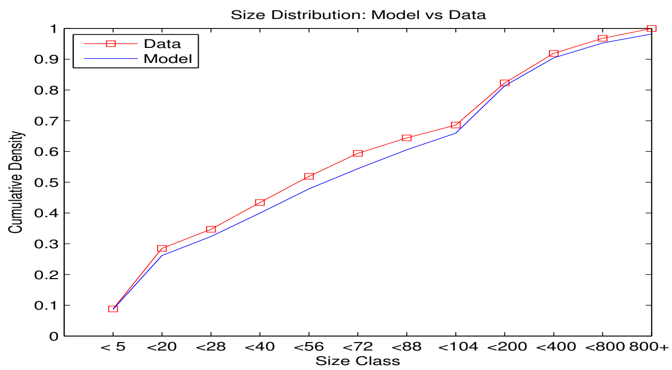


Figure 3: Calibrated Size Distribution

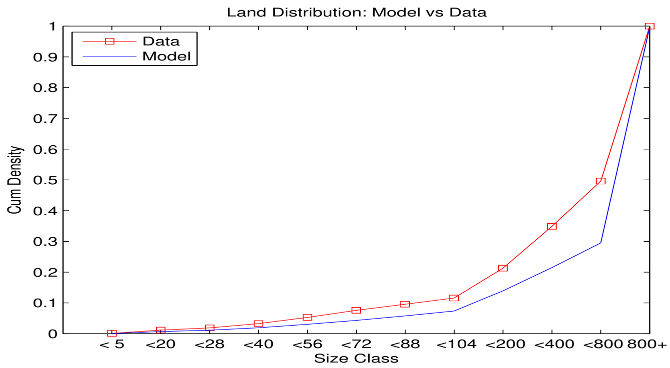


Figure 4: Implied Distribution of Land

B.4 Model Performances

1. Baseline Model Prediction

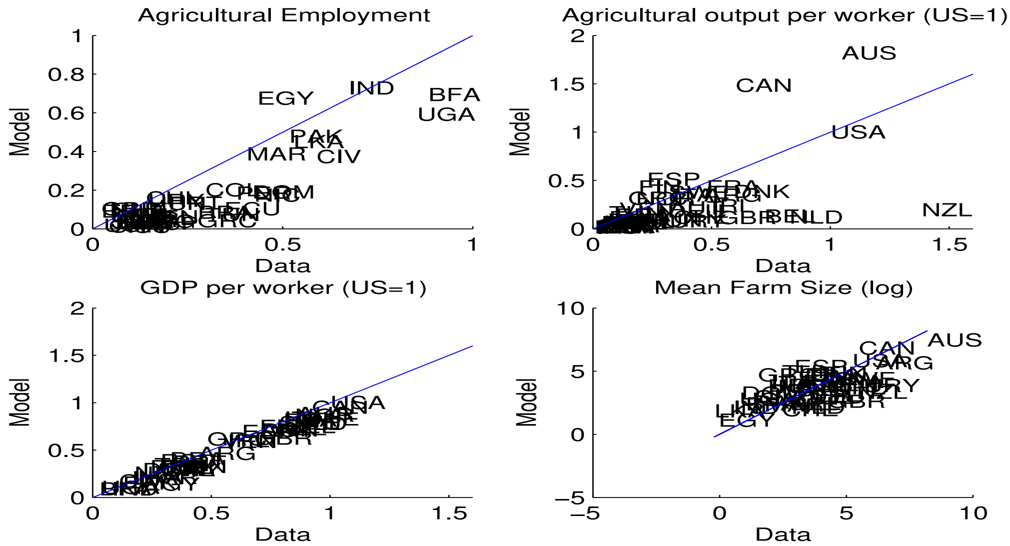


Figure 5: Model Prediction Against Data

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.

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)

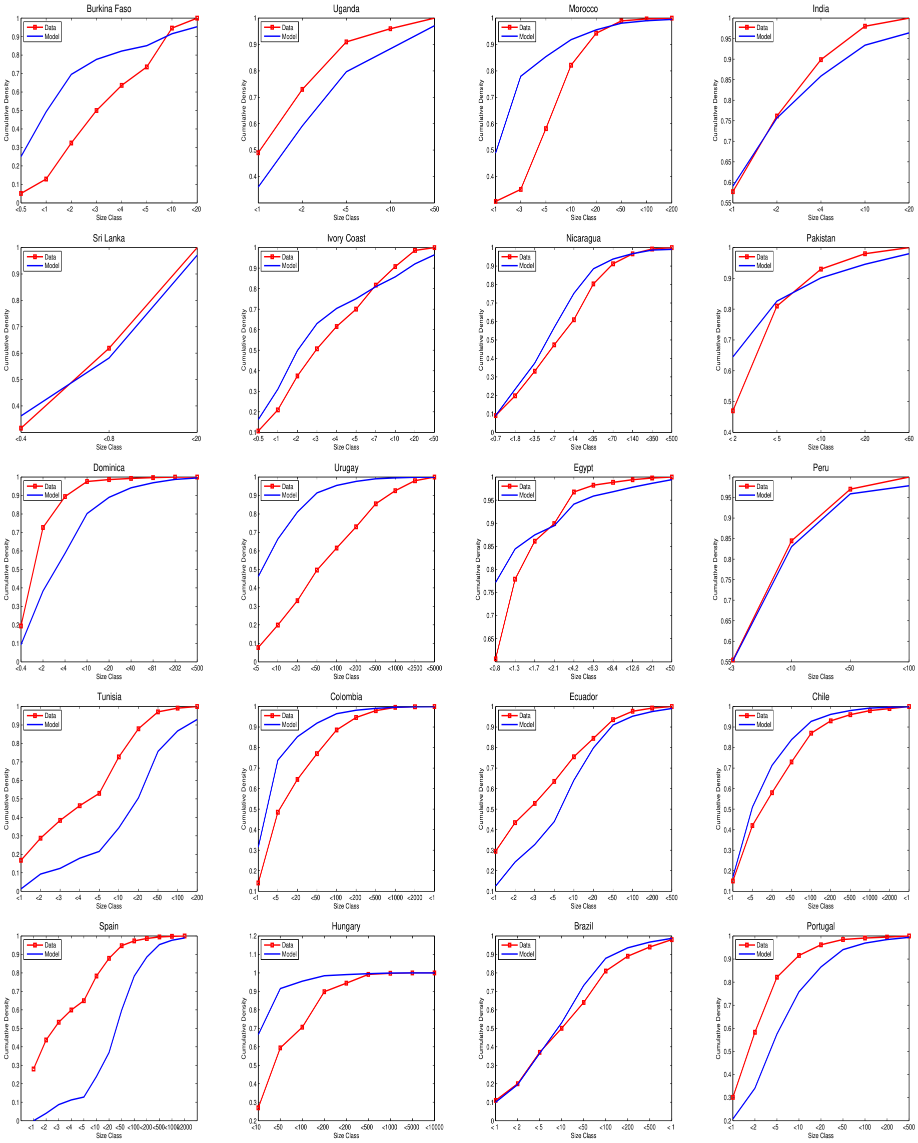
3. Model with Intermediate Inputs

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 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.

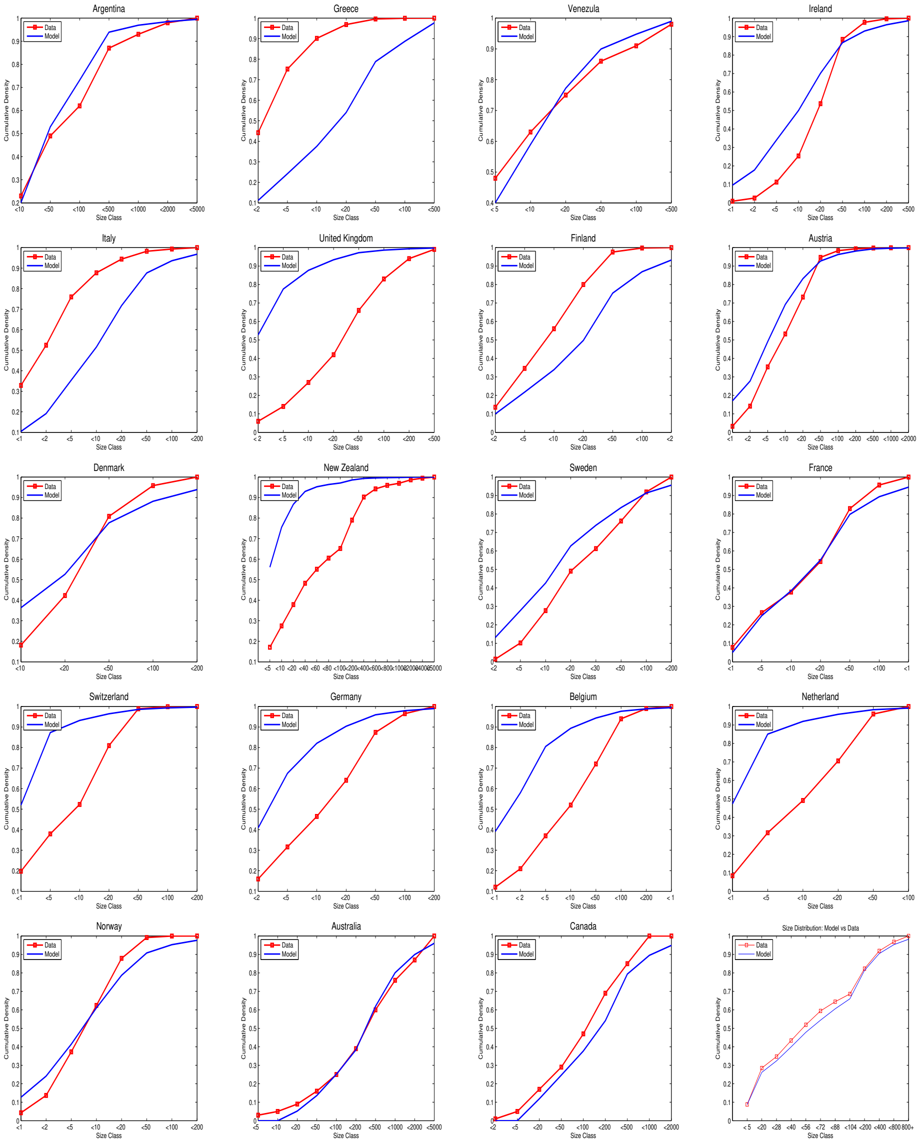
Exg. variable	L_a	ryala	mfs
$\bar{L}$ only	2.4%	1/1.2	88
A only	29%	1/17	18
π only	3.1%	1/1.6	135
A and $\bar{L}$	34%	1/20	7
A and π	49%	1/28	12
π and $\bar{L}$	3.6%	1/1.9	57
A, π and $\bar{L}$	58%	1/33	5
Data	70%	1/51	3

Table 9: TFP versus Endowment (With Intermediate)

B.5 Model Predicted Farm Size Distribution



B.6 Model Predicted Farm Size Distribution



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 World Census of Agriculture