Skill Investment, Farm Size Distribution and Agricultural Productivity

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Abstract

This paper quantitatively explains high labor share, low productivity and small farm size in agriculture of low income countries. I develop a variation of Lucas' span-of-control model. Specifically, I allow skill to grow over time as a result of optimal investment in a two-sector OLG model. The calibrated model is consistent with key features of the farming sector in the U.S. Given exogenous differences in nonagricultural productivity and land endowment, for a sample 40 countries, the model can explain almost all of the differences in agricultural productivity, and about 80% of the differences in labor allocation between the top and bottom quintile countries. Endogenously generated farm size distributions are close to actual ones for a large number of countries.

JEL Classification: O11, O13, O41

Keywords: Income differences, agricultural productivity, skill investment, farm size distribution.

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1 Introduction

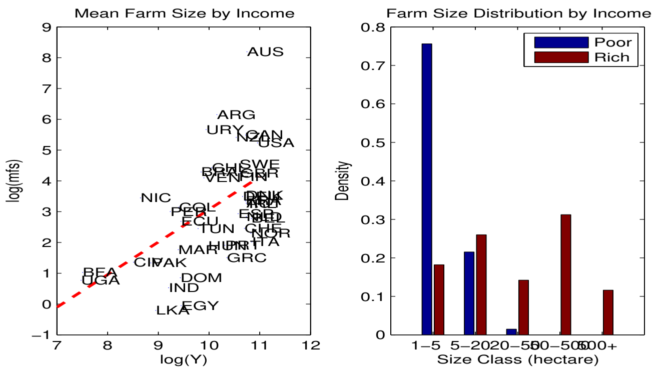
Recent studies have put agriculture at the center of understanding economic growth and income differences[1]. As pointed out in Restuccia et al. [2008], high employment share and low labor productivity in the agricultural sector is the main driver of low aggregate productivity in developing countries. Hence the central question is why most people in these countries work in a disproportionately unproductive sector. A counterfactual calculation similar to the one in Caselli [2005] will illustrate this point succinctly. If all countries would have the U.S. agricultural productivity, and maintain their own labor allocation and nonagricultural productivity, cross-country income differences would almost disappear. A less ambitious experiment, in which all countries have the U.S. relative productivity (agriculture/nonagriculture) and maintain their own labor share and nonagricultural productivity, would shrink income differences to a factor of 6, from a factor of 32, between the 90th and 10th percentile countries.

This paper provides a quantitative theory of agricultural productivity by focusing on scale of production. The approach is motivated by observations from World Census of Agriculture (WCA [1990,2000]) compiled by the Food and Agriculture Organization. I focus on comparison of holding size across countries. In WCA, a holding is defined as "an economic unit of agricultural production under single management comprising all livestock kept and all land used wholly or partly for agricultural production purposes, without regard to title, legal form, or size". The main finding is that mean holding size positively and strongly correlates with income level. Figure 1 (left panel) plots mean farm size (log) against log income per worker in 1996. Mean farm size ranges from below 1 hectare in the poorest countries to above 1000 hectares in the richest countries. Moreover, agricultural production in low income countries concentrates disproportionately on very small farms. Figure 1 (right panel) plots the farm size distributions of two representative countries [2]. In Uganda, for example, 73% of the farms are of scale less than 5

[1] Hansen and Prescott [2002], Gollin et al. [2004, 2007], Restuccia et al. [2008], among others

[2] Rich countries: U.S, Canada, Australia, Norway, Switzerland. Poor countries:

hectares. In contrast, 50% of the farms in the U.S. exceed 50 hectares in size. Observed variation in scale of production has profound implication about cross-country differences in agricultural productivity. Using development accounting, I show that differences in farm size distribution can account for 30% of the variations in agricultural productivity in a sample of 40 countries (see Appendix 5.2).



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

Figure 1: Size of Farms Across Levels of Development

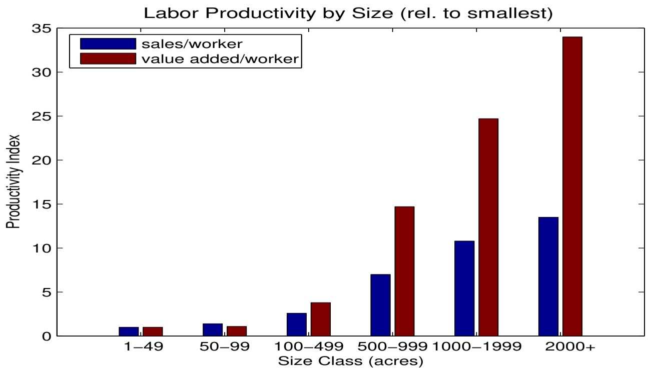
Why does the scale of operation matter for understanding productivity differences in agriculture? Cross-section data from the U.S. show that larger farms have higher measured productivity. If one compares average output per worker of farms in different size classes, the differences in labor productivity are marked (see Figure 2). In 2007 census, a 2000+-acre farm on average produces 16 times more output per worker than a 50-acre farm. In value added terms, the productivity differences are even more pronounced[3] Similar results are obtained when earlier censuses (92, 97 and 02) are used [4]. Taking the size-productivity regularity as given - without a theory that

Uganda, Burkina Faso, Ivory Coast, Pakistan, Sri Lanka.

[3]Differences in capital stock fail to justify observed labor productivity differences under reasonable factor shares. Computed Solow residual ranges from 3 to 5 times higher in the largest farms, relative to the smallest ones.

[4]Historical census also shows an increasing productivity gap between small and large farms. Cross-country data are limited, see Fan and Chan-Kang [2005] for a set of asian

explains why, it is clear that differences in the composition of farms will map into differences in productivity. In Appendix 5.2, a calculation of this kind shows that observed heterogeneity in farm size distribution can explain up to 30% of observed variation in agricultural productivity for a sample of 40 countries.



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

Figure 2: Productivity by Size of Farm

I deviate from the standard model by allowing skill accumulation in a dynamic environment. This modification serves three purposes. First, it allows calibrating the model to the observed farm size distribution in the U.S, and hence provides reasonable identification of the underlying distribution of skill types. Second, the model with skill accumulation is consistent with another cross-section data in U.S. farming - older operators operate large farms than younger peers. Table 5 in Appendix shows that heterogeneity in holding size over operator's life cycle is nontrivial and robust over time. Lastly, many economists argue the central role of human capital accumulation in economic growth and development [5]. In the model skill can be viewed as a form of human capital that is specific to agricultural production. Modeling the dynamics hence provides an additional avenue of

countries; Byiringiroa and Reardon [1996] for Rwanda, and Clark [1991] for historical England

[5]Lucas [1988], Manuelli and Seshadri [2005], Erosa et al. [2007], among others

understanding cross country differences in agricultural productivity. Indeed, the model predicts that farm operators in low income countries spend less time accumulating skills and experience slower growth in productivity over time. At the aggregate, suboptimal investment in skill improvement further reduces labor productivity.

This paper is related to a large literature that studies cross country income differences, eg., Hall and Jones [1999], Hansen and Prescott [1998], Klenow and Rodiguez-Clare [1997]. A strand of the literature stresses the importance of the agricultural sector in understanding aggregate income differences. Crdoba and Ripoll [2005] show that ignoring the agricultural sector results in substantial bias in imputed aggregate TFP. Chanda and Dalgaard [2008] argue that most of the cross country differences in efficiency come from differences in relative efficiency between agriculture and nonagriculture. Vollrath [2009] shows that misallocations between agriculture and nonagriculture go far in explaining aggregate productivity differences. This paper differs from these studies in using a general equilibrium model with an explicit agricultural sector. Gollin et al. [2004] argues low agriculture productivity can be explained by unmeasured home production, which is relatively cheaper in the agricultural sector. Restuccia et al. [2008] argue that distortions in intermediate inputs are quantitatively important for understanding cross country differences in agricultural and aggregate productivity. Adamopoulos [2006] document large differences in transportation costs across countries, and show that theses differences can account for a sizable share of income differences. Using micro level data, Gollin and Rogerson [2010] investigate the role of transportation cost in economic development in Uganda. This paper differs from these studies in stressing the role of individual heterogeneity and self-selection. Waugh and Lagakos [2009] argue that low agricultural productivity is due to poor specialization. Both papers stresses the importance of self-selection. This paper focuses on farm size heterogeneity, and use farm size distribution to discipline underlying skill distribution. After completing the paper, a recent study by Restuccia and Adamopoulos [2009] was brought to my attention. Both papers focus on farm size heterogeneity across countries and use a version of

Lucas' span-of-control model to endogenously generate a size distribution. However, this paper highlights the role of skill accumulation in explaining cross country variation in farm size distribution and agricultural productivity, which is abstracted from in their paper. 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. In section 4 I conclude.

2 Model

2.1 Environment

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

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

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

2.2 Household Decision

In this economy, there are two occupations. Each member can either work as a worker or a farm operator. All workers, regardless of ability type, supply one unit of physical time in return of wage rate w. A farm operator combines her skill (z), labor (h_a) and land (ℓ) to produce agricultural output according to

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

where q denotes the rental rate of land and A represents the economy-wide efficiency. The residual profit, or return to skill, $\pi(z)$ is retained by the farm operator who supplies skill z to production. It is simple to show

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

where p is the price of agricultural output, relative to nonagricultural output, which is used as numeraire.

Unlike in the standard span-of-control model, skill can grow over time through investment. More specifically, the law of motion of skill is given by

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

where s_t is the fraction of physical time denoted to skill augmentation. This technology highlights a trade-off between current and future income, as in most human capital accumulation process. An individual with skill z_t and invests s_t can only supply $z_t(1-s_t)$ units of skill to market production. Higher investment today reduces current income, but increases future income flow. Note that this technology assumes time as the sole input . This is done for several reasons. First, it allows for closed-form solutions and clearer expositions. Second, data on time allocations of farm operators are available to discipline relevant parameters. Lastly, data on resources investment by farm operators in skill accumulation are limited, if available at all.

When born, the household head decides the occupation for each member, and also the sequences of skill investments so as to maximize discounted household income. The occupations can't be changed over time. Since I focus on the stationary equilibrium, this assumption is harmless. The following lemmas establish some simple yet important results that characterize the stationary equilibrium, where all prices are constant.

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

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

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

The proof is given in Appendix. The lemma implies all farm operators, regardless of skill type, face the same skill profile over the life cycle. 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. Clearly, $\{x_t\}$ is independent of type. This allows a simple expression of lifetime discounted income of a type z farm operator

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

Note that $Y_f(z)$ is linear and strictly increasing in skill type z. In contrast, 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 $z \leq \bar{z}$ become a worker, and household members with skill type $z \geq \bar{z}$ become a farm operator.*

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

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

2.3 Nonagriculture Firm's Optimization

There is a representative firm that produces nonagricultural output with a linear technology $Y_n = A \cdot H_n$. Two remarks are in order. First, efficiency parameter A augments both agricultural and nonagricultural production. Second, H_n represents raw labor 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 collection of prices (w, p, q, R), consumption and investment $(c_{at}, c_{nt}, s_t)_{t=1}^{T}$, factor demand $h_a(z), \ell(z), H_n$ such that: (1) given prices, $(c_{at}, c_{nt}, s_t)_{t=1}^{T}$ solve household income maximization problem; (2) given prices, $(h_a(z), \ell(z))$ solve farm operator's profit maximization problem, and H_n solve nonagriculture firm's profit maximization problem; (3) Prices are competitive; (4) All markets clear.

To solve for prices (p, q), I use indifference condition for the marginal operator and land market clearing condition.

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

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

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. Solving for optimal consumption bundles and aggregating over generations yields aggregate demand of

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

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

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

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

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 live for 5 periods. Assuming an annual discount rate of 0.96, I set $\beta = 0.96^{10}$. TFP for the U.S is normalized to be 1. Parameters in the agricultural production function are directly inferred from U.S. Agriculture Value Added data (see Appendix 5.3). 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 in Restuccia 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. Over the same period, return to land and labor are almost identical, which suggests $\alpha = 0.5$ is a consistent value.

I restrict the skill type distribution to be lognormal with mean μ and standard deviation σ. This leaves 5 parameters $(\bar{a}, \eta, \bar{L}, \mu, \sigma, \theta)$ to be chosen simultaneously to match moments of U.S. economy. From World Development Indicator, agriculture employs 2% of the labor force. I also target a long run agricultural employment share of 0.5%[6]. This corresponds to the asymptotic agricultural employment share when subsistence consumption share of income is effectively zero.To discipline θ I turn to data on time allocations of farm operators. Census of Agriculture reports the number of days *off* the farm for operators in 5 different age groups: 25-34, 35-44, 45-54, 55-64, 65+. From there I compute the fraction of total working days supplied by operators from different age groups at a point of time (see Appendix 5.4). Within the model, this statistic corresponds to $\frac{1-s_i}{\sum_{i=1}^{T} 1-s_i}$ because operators of age i spend $(1 - s_i)$ fraction of time to farm production. 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[7]. Finally the model is also asked to reproduce the observed size distribution of farms in the U.S. Parameter values are summarized in Table 6 in Appendix. Figure 3 plots the calibrated size distribution against data. By construction, the model generated size distribution matches the data well. In addition, as depicted in Figure 4 in Appendix, the model also implies a land size distribution that

[6] Similar calibration strategies are used in Restuccia et al. [2008] and Waugh and Lagakos [2009]

[7] See Table 7 in Appendix

fits data very well, even though it is not targeted. The model also generates a distribution of hired labor over size class that is reasonably close to data [8].

3.1 Quantitative Experiment

In this section I test the model's ability to quantitatively explain high labor share, low productivity and small farm size in agriculture in low income countries. Data on sectoral productivity, sectoral labor shares and land endowment are from Restuccia et al., 2008. Mean farm size is calculated from the World Census of Agriculture (round 1990, 2000) published by Food and Agriculture Organization. These two data set, however, are not directly comparable because of time period differences. While the data in Restuccia et al,. pertains to year 1985, farm size data ranges from 1980-2000 (see 10 for country specific census date). Here I make a strong assumption that farm size distribution remains relatively stable over the period of time.[9]. As a first pass, I merge these two data sets to obtain a sample of 40 countries. In the following quantitative exercise, 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 skill types. For country i, I compute TFP A_i and land endowment $\bar{L}_i$ as follows

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

where $ynln_i$ is Nonagriculture GDP per worker of country i, and $LER_i =$ Land-employment ratio of country i, which is directly available from Restuccia et al., 2008 as well.

For evaluating model performance, I focus on the following metrics: agricultural labor share (La), real agricultural output per worker ($ryala$), real

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

[9] This assumption is probably reasonable for rich and poor countries, but not for transition countries

GDP per worker (rgdp) and mean farm size (mfs). Note that agriculture worker include both workers working in the agricultural sector and farm operators. Because relative price of agricultural output differs across countries, U.S price is used as international price when computing aggregate output. To facilitate comparison between model predictions and data, I divide countries in the sample into quintile by GDP per worker in the data. Productivity in the richest quintile (Q.5) is normalized to be 1. The sample consists of 40 countries[10]. 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 explains well the data in the four aspects I focus on. 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. Exogenous differences in TFP account for about 20% of the gap in agricultural productivity, and the remaining is accounted by the model through two channels. First, lower TFP pushes up equilibrium price of agricultural output, and renders farming more attractive than wage work for member with low skill. This pushes down equilibrium average skill of operators and agricultural productivity. Second, interest rate has to go up to offset excess demands in nonagricultural consumption. Higher interest depresses incentive to accumulate skill, and further reduces average skill of

[10] 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

farm operators. Model predictions are close to the data for other quartile countries. An notable exception is high income country (Q.4), for which the model substantially under-predicts agricultural productivity[11]. Since the level of skill is positively correlated with the optimal scale of production, the model also generates increasing mean farm size with income level, as observed in the data. One important feature of this model is its ability to reproduce not only the first moments, but also the entire *farm size distribution* across countries. In Appendix 5.8 I plot the model predicted farm size distributions along with their empirical counterparts for all countries in the sample. Even though *ex ante* all countries face the same skill-type distribution, the *ex post* size distribution of farms exhibits substantial variations across levels of income. For a large set of countries the model generated size distribution is amazingly close to the data.

High employment and low labor productivity in agriculture are jointly driving low income. It is thus important for the model to be consistent with data in terms of sectoral labor allocation. For the top quintile countries, the model correctly predicts the employment share in agriculture. For the bottom quintile countries, the model predicts a 48% agricultural employment share, about 80% of the actual share. For low income countries (Q.2), the model also predicts a lower agricultural labor share, compared to data. This reflects other forces at work. For example, high price of intermediate inputs, as discussed in Restuccia et al., 2008, induces farm operators to substitute labor for modern input. This model also abstracts from labor market distortions, while in low income countries barriers to sectoral labor movements are common as evidenced by substantial gap in earnings. One famous example is the *Hukou* system in China that imposes institutional restriction on immigration from rural villages to urban cities. My results show that these distortions are also important for understanding sectoral labor allocations. Another stylized fact about economic development is declining importance of agriculture in aggregate output - one available measure is agriculture value added as a percentage of GDP. For the top quintile, the model pre-

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

dicts agricultural output to be 10% of aggregate 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%. Finally, the model predicts a higher relative price of agricultural consumption in low income countries. The ratio between the poorest (Q.1) countries and the richest (Q.5) countries is 2.8 in the model. Using ICP data from the World Bank, I compute the relative price between "agricultural consumption" and "nonagricultural consumption" for all available countries[12]. The relative price in 2005 is around 4 times higher in the 10th percentile country, compared to the 90th percentile country.

Recall that in the model, countries are different in two dimensions: TFP and land endowment. Which exogenous variable is relatively more important in determining productivity? To shed light on this question, I perform a series of counterfactual experiments for a hypothetical country that represents the poorest countries in the sample[13]. Relative to the U.S, the representative poor country has 4.5 times lower TFP, and 2.1 times smaller land endowment. To disentangle the relative contribution, I change one exogenous variable at a time. Table 2 summarizes the results.

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

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, though mean farm size drops by roughly a half. Differences in endowment alone can't go far in explaining differences in labor allocation and productivity. In contrast, if inferred TFP is reduced - with land endowment

[12] "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 and Lagakos [2009]

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

unchanged, there is a massive movement of labor into the agricultural sector. Moreover, agricultural productivity drops by a factor of 22, and mean farm size drops further to 47 hectares. TFP thus has a more profound impact on equilibrium allocations. It is also interesting to note that the decomposition of TFP and land endowment is not orthogonal. If both TFP and land endowment are reduced, the representative poor country allocates 53% of the labor force to agriculture. Output per worker drops massively - by a factor of 48. An average farm is only about one tenth the size of an average farm in the U.S..

3.2 Discussion

A novel and crucial feature of the model is to embed skill accumulation in an otherwise standard Lucas's span-of-control model. U.S. cross section data suggests that farm operators become more productive over the life cycle. A standard human capital accumulation theory, when applied to the farming sector, can reconcile the observed patterns. Data on time allocation of farm operators also support this interpretation. Using the model, I test the idea for a cross-section of countries. In the quantitative exercise, the model is calibrated to the observed U.S. farm size distribution. It turns out that the ability of the model to reproduce empirical farm size distribution critically hinges on skill accumulation. 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. To investigate the quantitative importance of skill accumulation in determining equilibrium outcomes, I recalibrate the model absent skill accumulation. Then I ask the model to predict for the representative poor country. The model without skill accumulation in general explains less of the cross-section differences in labor share and output per worker in agriculture. Details of calibration and results are postponed in Appendix

5.6.

The notion of aggregate efficiency in the model potentially encompasses various sorts of distortions such as institutions, market incompleteness, labor market distortions, etc. The nature of these distortions are not spelled out in this study. More importantly, these distortions are not specific to the agricultural sector. This contrasts with other studies that focus on distortions geared towards the agricultural sector. One important and convincing study of this kind is Restuccia et al. [2008], who show barriers to intermediate inputs have sizeable impact on labor allocation and productivity. Here I consider a variation of the model that incorporates specifically distortions in intermediate inputs (X). The technology in the agricultural sector is given by

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

One unit of nonagricultural output can be consumed or converted into intermediate good at the rate of π. For expositional purposes, I abstract from skill accumulation to disentangle the effects coming from distortions from those stemming from skill investment. Detailed calibration and results are given in Appendix. The main finding is that barrier to intermediate inputs account for a sizeable share of differences in agricultural productivity. Moreover, high price of intermediate inputs also reduces the mean farm size.

Several remarks on the limitation of the model are in order here. Firstly, calibrated share of land in agriculture production is considerably large, compared to common values used in the literature[14]. In addition, land endowment is approximated by land-employment ratio, which abstracts from possible differences in the quality of land. In the model, TFP represents the economic-wide efficiency. However, in the quantitative analysis, it is approximated by nonagricultural output per worker. While this approach appears reasonable for rich countries where minimum resources are devoted to the

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

agricultural sector, it is deemed less appropriate for poor countries where most of the economic activity takes place in the traditional sector.

4 Conclusion

In this paper I develop a model that links agricultural productivity to the skills of farm operators. In poor countries, subsistence need and low wage rate renders farming a better option for even low skill individuals. As a result of self-selection, a large fraction of the labor force work in the traditional sector. Moreover, the average farm operator has low skill and hence low measured labor productivity. Since optimal scale of production is tied to the skill of the operator, an additional implication is increasing farm size with income level. The model is thus able to reconcile simultaneously high labor share, low productivity, and small farm size that characterizes the agricultural sector in poor countries. When skill is allowed to grow over time through optimal investment, 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.

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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*

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

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

$$R^{1-t} = \lambda_t \theta s_t^{\theta - 1} \tag{7}$$

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

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

λ_{T-1} and s_{T-1} does not depend on z_{T-1}. Repeating this argument implies that the entire path of investment is independent of initial skill type.

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

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

where Y is the discounted lifetime income. The Lagrangian is

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

F.O.C yields

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

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

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

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

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

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

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

Substitute F.O.C into budget constraints we have

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

Aggregate consumption at a point of time is given by

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

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

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

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

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

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

5.3 Estimating Return to Scale Parameters in Agriculture

Based on data from USD [1980-1989], 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. For the period 1980-1999, the estimated income are given in the table blow.

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

Table 3: Factor Shares in U.S. Farming

5.4 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 (Panel A). To compute the the hours supplied by operator of a certain age, I assume 250 working days a year. In addition, I use the midpoint of the interval as the average days off farm. For example, "None" in the table means operators work 250 days a year. Operators work 200 days if in interval " 1-99 days", 150 working days if in interval "100-199 days", and 25 working days if in interval "200 days+". This allows me to compute the total number of working days a year for operators in any age category. Finally, I compute the share of days supplied by operators in age group i (Panel B) as $s_i = \frac{wd_i}{\sum_{i=1}^{I} wd_i}$, where wd_i is the number of working days for operators in age group i.

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

Table 4: Days off Farm by Age of Operator

Age	25-34	35-44	45-54	55-64	65+
1992	602	838	921	785	562
1997	654	872	997	807	589
2002	490	632	807	678	678
2007	575	857	909	736	542

Source: U.S. Census of Agriculture, Vol 1, Chapter 1: Table 48(92,97), Table 60(02), Table 63(07).

Table 5: Mean Holding Size by Age of Operator

5.5 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	1.23	0.34
Model	0.08	0.16	0.21	0.26	0.29

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

Figure 3: Calibrated Size Distribution

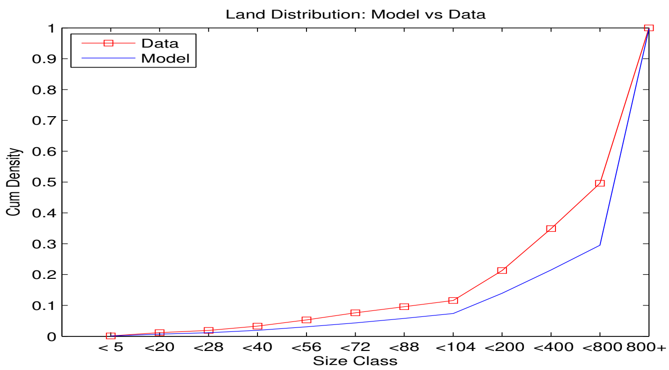


Figure 4: Implied Distribution of Land

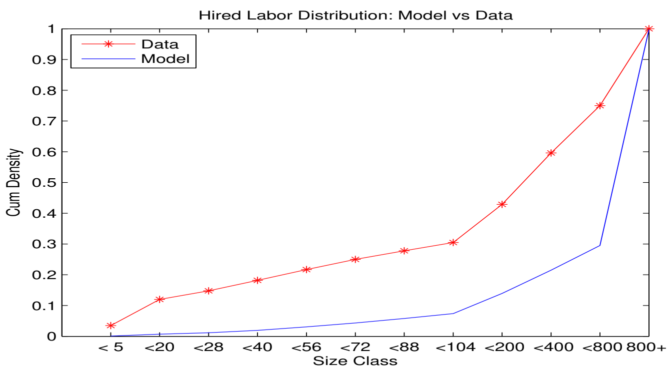


Figure 5: Implied Distribution of Hired Labor

5.6 Model Performances

1. Baseline Model Prediction

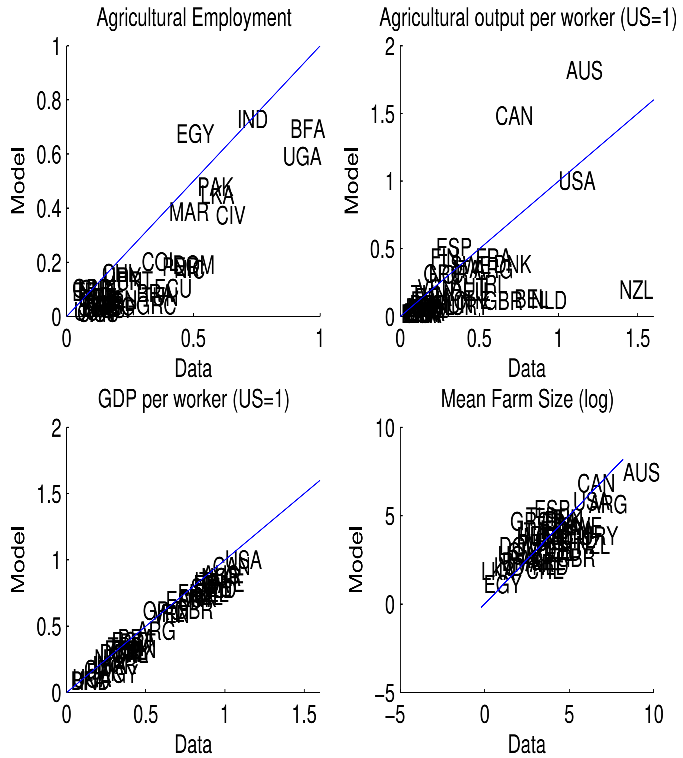


Figure 6: Model Prediction Against Data

2. Model without Skill Accumulation

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

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)

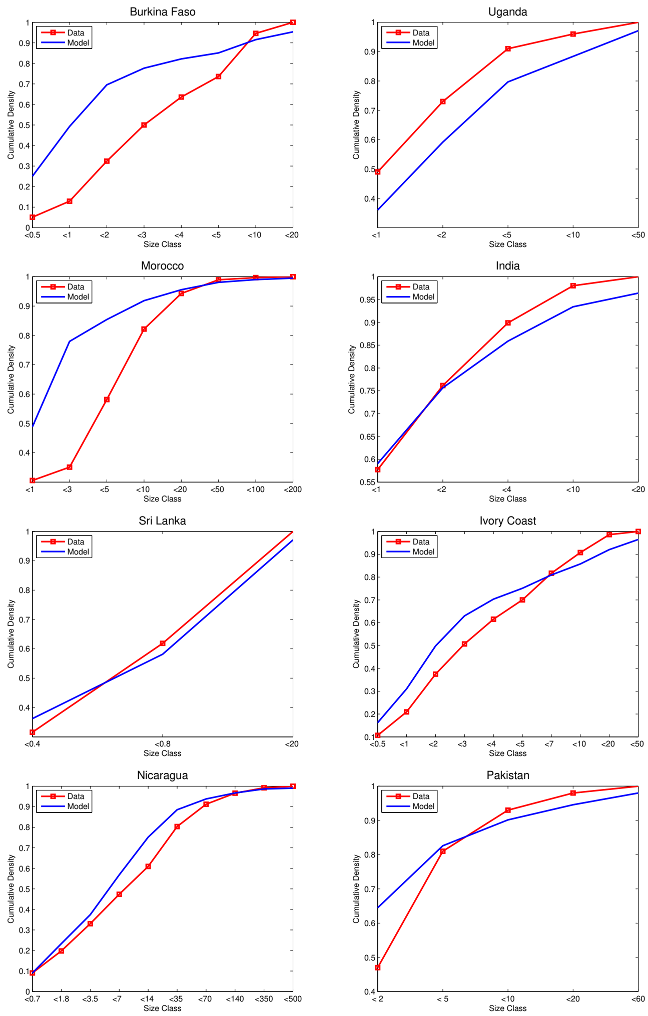
3. Model with Intermediate Inputs

I set $\gamma = 0.8$, $\phi = 0.5$ and $\rho = 0.2$. For the U.S, $\pi = 1$. I choose $(\eta, \bar{;}\mu, \sigma)$ 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.

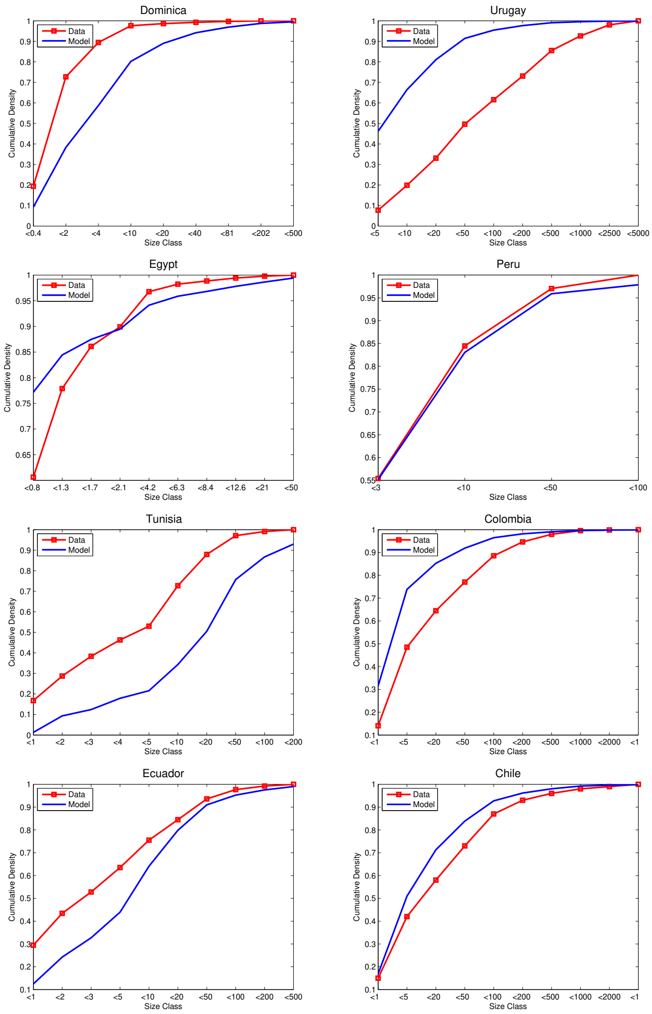
Exg. variable	L_a	$ryala$	mfs
$\bar{L}$ only	2.4%	1/1.2	88
A only	29%	1/17	18
π only	3.1%	1/1.6	135
A and $\bar{L}$	34%	1/20	7
A and π	49%	1/28	12
π and $\bar{L}$	3.6%	1/1.9	57
A, π and $\bar{L}$	58%	1/33	5
Data	70%	1/51	3

Table 9: TFP versus Endowment (With Intermediate)

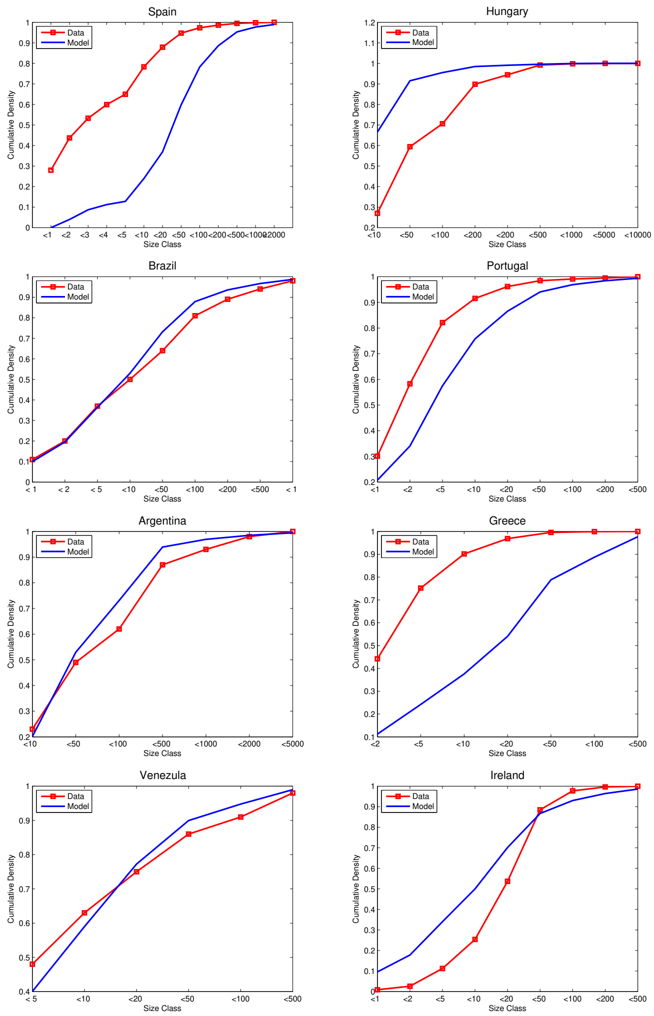
5.7 Model Predicted Farm Size Distribution (Q.1)



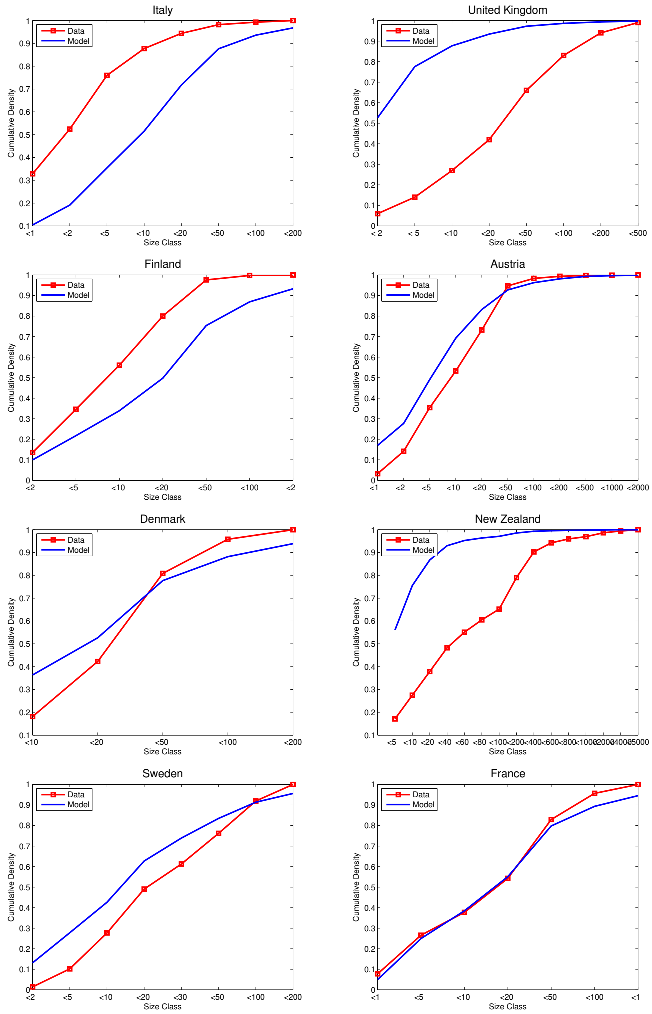
5.8 Model Predicted Farm Size Distribution (Q.2)



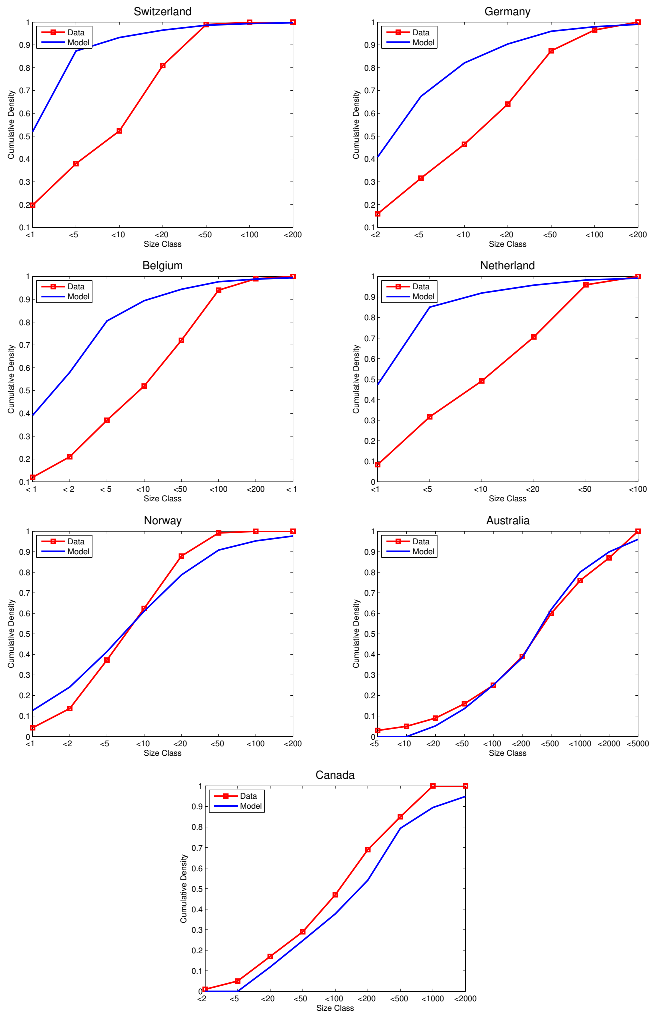
5.9 Model Predicted Farm Size Distribution (Q.3)



5.10 Model Predicted Farm Size Distribution (Q.4)



5.11 Model Predicted Farm Size Distribution (Q.5)



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

Table 10: Summary Statistics of WCA