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Skill accumulation and international productivity differences across sectors

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SKILL ACCUMULATION AND INTERNATIONAL PRODUCTIVITY DIFFERENCES ACROSS SECTORS

by

Wenbiao Cai

An Abstract

Of a thesis submitted in partial fulfillment of the
requirements for the Doctor of Philosophy
degree in Economics
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July 2012

Thesis Supervisor: Professor B. Ravikumar

ABSTRACT

Why some countries are so much richer than others is a question of central interest in economics. Low aggregate income per worker in poor countries is mostly accounted for by low labor productivity and high employment in agriculture. This thesis attempts to understand cross-country income difference through examining productivity differences at the sector level - in agriculture and in non-agriculture.

Between rich and poor countries, there is a 45-fold difference in agricultural output per worker and a 34-fold difference in mean farm size. In the first chapter, I argue farmer's skill as a plausible explanation for these differences. The model features heterogeneity in innate agricultural skill, on-the-job skill accumulation, and span-of-control in agricultural production. I show that low total factor productivity (TFP) in poor countries not only induces more individuals with low innate skill to choose farming, but also reduces the incentive to accumulate skill. Between rich and poor countries, the model generates substantial difference in farmer's skill, which translates into differences in agricultural productivity and farm size distribution. Quantitatively, the calibrated model explains half of the cross-country differences in agricultural output per worker, and successfully replicates the size distribution of farms in both rich and poor countries.

Cross-country productivity differences are asymmetric across sectors. The labor productivity gap between rich and poor countries in agriculture is twice as large as that in the aggregate, and ten times larger than that in non-agriculture. The second chapter shows that these sectoral productivity differences can arise solely from difference in aggregate TFP. I extend the framework in the first chapter to allow for different skill in non-agricultural production as well. Low TFP distorts the allocation of skills across sectors and discourages skill accumulation on the job. To discipline the initial skill distribution and skill accumulation, the model is calibrated to match earnings distribution and age-earnings profiles in both agriculture and non-agriculture in the U.S. The model's implications are then examined using a sample of 70 countries that covers a wide range of development. Between rich and poor countries, the model accounts for most of the productivity differences at the sector level - productivity difference in agriculture in the model is 1.8 times larger than those in the aggregate and 6 times larger than those in non-agriculture. As in the data, the share of farmer in the labor force in the model declines from 85 percent in the poorest countries to less than 2 percent in the richest countries. These results suggest that policy aiming at improving overall efficiency should be prioritized.

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CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

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has been approved by the Examining Committee for the thesis requirement for the Doctor of Philosophy degree in Economics at the July 2012 graduation.

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To my sweet gril Connie

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Between rich and poor countries, there is a 45-fold difference in agricultural output per worker and a 34-fold difference in mean farm size. In the first chapter, I argue farmer's skill as a plausible explanation for these differences. The model features heterogeneity in innate agricultural skill, on-the-job skill accumulation, and span-of-control in agricultural production. I show that low total factor productivity (TFP) in poor countries not only induces more individuals with low innate skill to choose farming, but also reduces the incentive to accumulate skill. Between rich and poor countries, the model generates substantial difference in farmer's skill, which translates into differences in agricultural productivity and farm size distribution. Quantitatively, the calibrated model explains half of the cross-country differences in agricultural output per worker, and successfully replicates the size distribution of farms in both rich and poor countries.

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CHAPTER 1
FARM SIZE DISTRIBUTION AND AGRICULTURAL PRODUCTIVITY ACROSS COUNTRIES

1.1 Introduction

This paper is about explaining two observations across countries: 1) cross-country differences in labor productivity in agriculture are enormous; and productivity differences in agriculture are larger than those in other sectors of the economy; 2) the size distribution of farms differs systematically across levels of development. Small farms (as measured by land size) account for most of the farms, as well as most of the land in developing countries.

The first observation is not exactly new. Kuznets (1971) documents this empirical feature for a small set of countries. Later on Caselli (2005) and Restuccia, Yang, and Zhu (2008) do so for a larger sample of countries. As of 1985, the difference in real output per worker in agriculture between rich and poor countries exceeds a factor of 45, which is 10 times larger than that in non-agriculture.[1] On the other hand, most of the labor force is absorbed in the least productive agricultural sector in developing countries. Hence, understanding low agricultural productivity is key to understand aggregate income differences.

The second observation is less well known. Data on farm size distribution is made available by the Food and Agriculture Organization (FAO) through its release of

[1] Gollin, Lagakos, and Waugh (2011) attempt to correct measurement errors in sectoral productivity series. They find that, given the best available information, large productivity gap remains.

the World Census of Agriculture. FAO collects and processes national agriculture census and presents key summary information in an internationally comparable format. There are two reasons why this paper focuses on farm size. First, labor in agriculture is mostly self-employed. Hence, scale and production of a farm is closely related to the productivity of individuals operating it. Second, there is ample evidence suggesting a robust positive correlation between farm size and labor productivity. Cornia (1985) found a positive correlation between farm size and labor productivity for a set of developing countries.[2] For the U.S., I provide strong evidence showing that larger farms exhibit higher productivity. As a result, understanding differences in farm size distribution across countries can be informative about labor productive differences in agriculture.

This paper reconciles these two observations in a model in which unmeasured skill of farmers plays a key role. Low labor productivity and small-scale production in agriculture reflect poor farming skill of farmers in low income countries. Differences in skill of farmers arise endogenously in the model, given exogenous differences in total factor productivity (TFP) and land endowment. In particular, an economy with low TFP or poor land endowment features a large labor force in agriculture with poor skill in farming.

I construct a lifecycle model where each cohort consists of a continuum of heterogeneous agents. Individuals differ in their skill in agricultural production when

[2]See also Clark (1991), Byiringiroa and Reardon (1996), Fan and Chan-Kang (2005) for studies of individual countries.

born. The initial skills are modeled as random draws from a fixed distribution. However, individuals can improve their skill over lifecycle by allocating time away from production. Individuals choose either to become a farmer or a worker. Their skill is useful as a farmer but irrelevant as a worker. This occupational choice is made at the first date and assumed to be irreversible over lifecycle. In such an environment, labor productivity in agriculture depends critically on both the initial skills of farmers and their skill accumulation over lifecycle.

A key feature of the model is that preferences are non-homothetic, i.e., there is a minimum consumption of agricultural good. Non-homothetic preferences give rise to two implications. The first one is that the share of labor in agriculture decreases with income. This feature is standard in the literature of structural change, e.g., Laitner (2000), Kongsamut, Rebelo, and Xie (2001), Gollin, Parente, and Rogerson (2007). Importantly, this standard feature has another dimension when individuals have heterogenous skills. Specifically, as more individuals enter agriculture the marginal farmer also moves further down the distribution of *initial* skill. In other words, in low income countries many of the farmers do not have comparative advantage in agriculture. The second implication is that the inter-temporal elasticity of substitution is low when income is low. The marginal utility from consumption of agricultural good (and hence, the marginal cost of investment in skill improvement) is high precisely when income is low. Skill accumulation is hence discouraged in low income countries. As a result, the average farmer in low income countries not only have low initial skill, they also experience little skill growth over time. Between rich and poor countries, there are potentially large differences in unmeasured skill of farmers. Consequently, these differences in skill lead to differences in measured labor productivity and scale of production in agriculture.

To explore the quantitative implications of the model, I first calibrate it to the U.S. The model is parameterized to reproduce the size distribution of farms, time allocation of farmers, and other macroeconomic statistics in the U.S. I test the model using a sample of 50 countries, covering a wide range of development. Since the question of interest is why cross-country productivity differences in agriculture are larger than those in non-agriculture, I compute country-specific TFP such that the model matches real output per worker in non-agriculture for each country. Hence, the model is silent on the sources of productivity differences in non-agriculture. As implications, the model speaks to the allocation of labor between sectors, output per worker in agriculture, and also endogenously generates a non-degenerate size distribution of farms. I examine these predictions against data. I find that the model explains roughly 50 percent of the cross-sectional differences in real output per worker in agriculture. I also find the model successfully captures cross-country differences in farm size distribution: 1) mean farm size increases with agricultural productivity. In the data, the correlation between PPP output per worker in agriculture and mean farm size is 0.45. In the model, it is 0.6; and 2) the size distribution of farms is heavily skewed to the left in developing countries. For the poorest 5 percent countries, for example, the share of farms with less than 5 hectares of land is 89 percent in the data. The model predicts a share of 87 percent. For many countries, the model actually matches the empirical farm size distribution fairly well, which I consider a success given the simple structure of the model.

This paper fits into an expanding literature that emphasizes the key role of agriculture in understanding cross-country productivity differences. Some focus on the implication about aggregate TFP such as Cordoba and Ripoll (2005), Chanda and Dalgaard (2008), Vollrath (2009). Others attempt to quantify the effect various distortions have on sector productivity such as Gollin, Parente, and Rogerson (2004), Restuccia, Yang, and Zhu (2008), Adamopoulos (2011) and Gollin and Rogerson (2010). As in Lagakos and Waugh (2010), this paper does not appeal to distortions geared specifically towards agriculture, but instead focuses on the efficiency of workers in agriculture. However, difference in efficiency of workers result also from skill accumulation in this paper. On the prediction of cross-country size distribution of farms, this paper is related to Adamopoulos and Restuccia (2011), who offer an alternative, and interesting, application of the span-of-control framework. In particular, they do not consider the division of heterogeneous family members into different occupations. Such specification allows them to isolate the effect of idiosyncratic policy distortions on total output in agriculture. As a result, the origins of productivity differences are not the same in these two papers. In their paper, productivity is low in agriculture because the most productive farms are not operating at the optimal scale, due to distortions. In the current paper, low productivity is due to a large share of unproductive farmers who do not invest to enhance their skill. All farmers, productive or not, are producing at their optimal scale. Secondly, these two papers also differ in their implications of the farm size distribution. In Adamopoulos and Restuccia (2011), the size distribution of farms is used to infer the distribution of idiosyncratic policy distortions. In this paper, the size distribution is a mapping from the distribution of farmer's skill. Hence the difference in the size distribution of farms reveals information about the difference in the skill composition of farmers. On stressing the role of unmeasured skill, this paper also relates to Assuncao and Ghatak (2003). However, their paper mainly focuses on the link between farm size and land productivity.

The remaining of the paper is organized as follows. Section 1.1 presents the facts that motivate this paper. Section 2 describes the economic environment. Section 3 explains the calibration strategies and presents the main results. Section 4 concludes.

1.1.1 Facts

Fact 1: farm size distribution varies systematically with income

First of all, mean farm size tends to increase with agricultural productivity. This is clear from Figure 1.1, which plots on the horizonal axis real output per worker in agriculture (relative to the U.S.), and on the vertical axis average farm size (as measured by land area in hectares). For the poorest 10 percent of countries, mean farm size is merely 2.6 hectares.[3] The average farm is almost 60 times larger (130 hectares) in the richest 10 percent of countries.[4] There is a factor of 50 differences

[3] Burkina Faso, Uganda, Nepal and Senegal

[4] U.S., Canada, Switzerland, Norway

in the average size of farms. Figure 1.2 plots two empirical farm size distributions. One for the poorest 10 percent of countries in the sample, and one for the richest 10 percent of countries. Most of the farms in poor countries are small in size. In fact, 73 percent of the farms are smaller than 5 hectares, and nearly all of the farms are less than 20 hectares. In contrast, the majority of farms exceed 20 hectares in size in rich countries, and 50 percent of the farms are over 50 hectares in size.

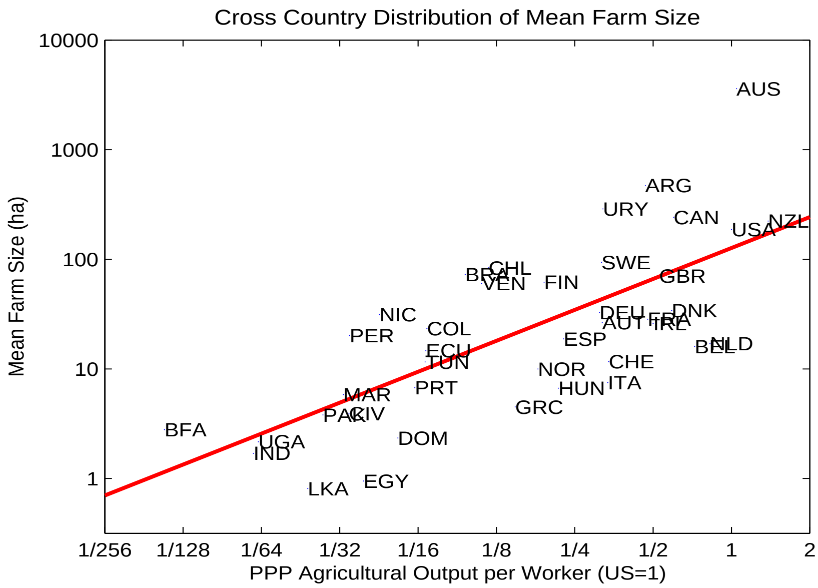

Figure 1.1: Cross-country distribution of mean farm size

Fact 2: larger farms exhibit higher labor productivity in the U.S.

I measure labor productivity for a cross-section of farms in 2007. Two measures of productivity are used. The first one is sales per worker, and the second one is value added per worker. In both cases, the productivity of the smallest farm is normalized

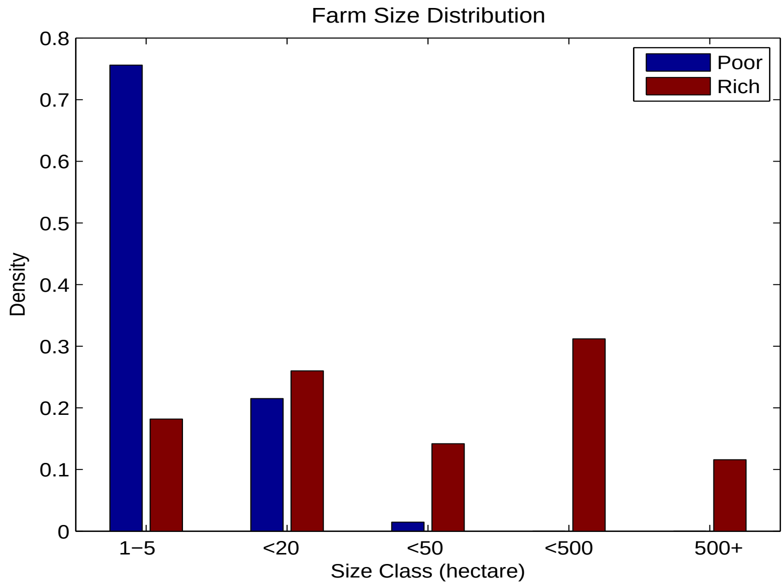

Figure 1.2: Farm size distribution in rich and poor Countries

to unity. Figure 1.3 plots the relative productivity against size classes. In either measure, labor productivity increases almost monotonically with size. Compare, for example, farm over 1000 hectares with farms less than 50 hectares. Value added per worker can differ up to a factor of 10.

Fact 3: age-productivity profile of U.S. farmers exhibits a hump shape

I show that productivity exhibits a hump shape over the lifecycle of U.S. farmers. I first measure farmer's productivity as output (net of government transfer) per farmer. This measured is labeled as "Measure I" in Table 1.1. I find that the productivity gain between age 25 and age 45 can be as large as a factor of 3. To verify whether these productivity differences simply reflect differences in other inputs, I compute a Solow-type residual using information on quantity of four factors of production:

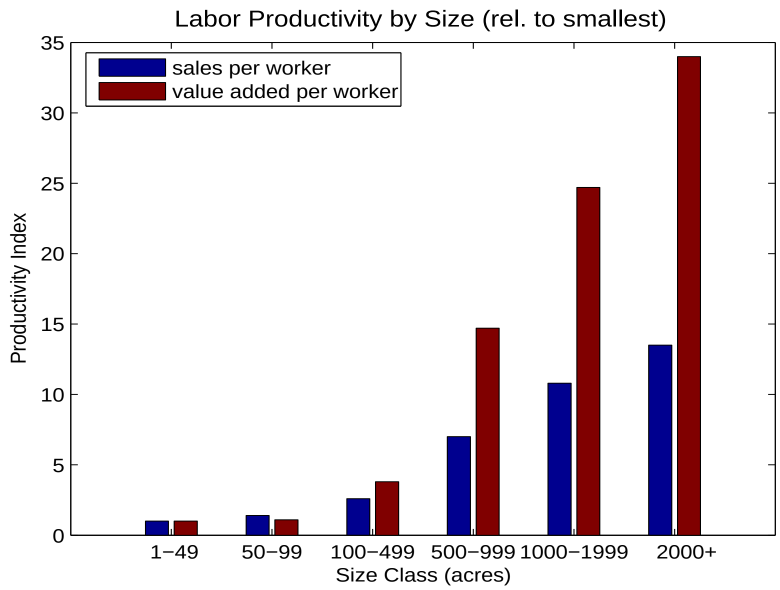

Figure 1.3: Labor productivity by farm size in the U.S. Data is from 2007 U.S. census of agriculture.

intermediate inputs, land, capital, and hired labor.[5] This is labeled as "Measured II" in Table 1.1. The elasticity of each factor of production is calculated from Table 5 and 6 in Valentinyi and Herrendorf (2008). I find that between age 25 and 45, there remains a large increase in productivity of roughly 35 percent.

[5]Intermediate inputs include feed, seed, chemical and fertilizers. Capital includes machinery, equipments, and buildings. Solow residual of operator i is computed as $y_i/(k_i^{\alpha_k} x_i^{\alpha_x} \ell_i^{\alpha_\ell} h_i^{\alpha_h})$, where y is output per operator. Factors of production $j = k, x, \ell, h$ denotes, respectively, capital, intermediate, land and labor. α_j is the respective elasticity.

Table 1.1: Age-productivity profile of U.S. farmers

Age	< 25	$25 - 34$	35-44	45-54	55-64
Measure I	1	2.02	3.00	2.88	1.96
Measure II	1	1.24	1.35	1.28	0.87

Note: data is from 2007 U.S. census of agriculture, Table 63.

1.2 Model

1.2.1 Environment

Each period a continuum (of measure one) of individuals are born, and live for T periods. Individuals of the same cohort form a household, with all decisions made by a hypothetical household head. The representative household derives utility from consumption of two consumption goods according to

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

where c_a is an agricultural good, and c_n is a non-agricultural good. Preferences are non-homothetic with $\bar{a} > 0$, in which case two implications follow. Firstly, the share of income spent on agricultural consumption declines with the level of income. This, of course, conforms with the "Engel's curve". Secondly, the inter-temporal elasticity of substitution is low when income is low. As will become clear later, these two implications are central to the results in this paper.

Each member within a household is endowed with one unit of time each period.

The economy has a fixed stock of land, denoted by $\bar{L}$, which is equally owned by households. There is no population growth or lifetime uncertainty. As a result, T is also the measure of the population size at any point in time.

1.2.2 Endogenous Skill Accumulation

Within a household, individuals differ in their skill in agricultural production. At age 1, individuals draw their skill type, $z \in \Re^{+}$, from a known distribution $G(z)$. These draws are $i.i.d$ across individuals and over time. Throughout the paper, an individual with an initial draw z is referred to as type z. Over the life cycle, individuals can increase their level of skills through skill accumulation. Hence, the age-profile of skill is endogenously determined within the model. Specifically, the level of skill evolves over time according to

$$z_{t+1} = f(z_t, s_t) = z_t + z_t \cdot s_t^{\theta}, \quad s_t \in [0, 1], \tag{1.1}$$

where s_t is the fraction of time allocated to skill accumulation. Equation (1.1) maps into an array of actions farmers undertake to improve productivity, such as experimenting with different seeds/crops/fertilizers, updating on the most recent available technologies, learning new equipments etc. Just like any other type of learning, these actions consume time. The process of human capital accumulation is the same as the one in Ben-Porath (1967), except that I do not consider goods input. While arguably certain skill-enhancing tasks may require input other than time - e.g., purchasing a new computer, I abstract from these considerations for the benefits of closed-form solutions and clearer expositions. Moreover, I use data on time allocations of farm operators to discipline relevant parameters, while generally information on other types of investment made by farm operators in skill accumulation are limited, if available at all.

1.2.3 Production

The production of agricultural good combines three inputs: skill, labor, and land, using a constant returns to scale technology:

$$y_a = A \cdot (z(1-s))^{1-\gamma} \left(h_a^{\alpha} \cdot \ell^{1-\alpha}\right)^{\gamma}. \tag{1.2}$$

In (1.2), h_a is labor, ℓ is land, and A is total factor productivity (TFP). Note that since skill is endogenous, the amount of skill used in production is discounted by the fraction of production hours, (1-s). The production of non-agricultural good, on the other hand, requires labor as a sole input in a linear fashion.

$$y_n = A \cdot H_n. \tag{1.3}$$

Note that skill does not matter in the production of non-agricultural good. In equilibrium, this implies a common wage rate for workers in non-agriculture.

1.2.4 Household Problems

There are two occupations in this economy. Each household member can either become a farmer or a worker. This occupation choice is assumed to be fixed over the life cycle.[6] The problem of a worker is simpler, and hence, is discussed first. The

[6] This assumption is not restrictive. Under zero skill depreciation, individuals will optimally not switch between occupations in a stationary equilibrium.

production technology in (1.3) dictates a common wage rate for all workers. Let w denote the market wage rate. Furthermore, since skill is not rewarded in the non-agriculture sector, it follows that workers do not accumulate skill over the life cycle.

A farmer operates the production technology in (1.2), rents labor and land from the market, and retain profit. The maximized profit, $\pi(z, s)$, depends on both the level of skill and hours devoted to production, i.e.,

$$\pi(z, s) = \max_{\{h_a, \ell\}} \quad p \cdot y_a - w \cdot h_a - q \cdot \ell,$$

where p is the price of agricultural output, and q is the rental price of land. Throughout the paper, non-agricultural output is used as a numéraire.

It is straightforward to show that $\pi(z, s)$ is linear in both z and s. Furthermore, the skill accumulation technology satisfies the Inada condition, i.e., $f_s(z, s) = \infty$ when $s = 0$. It follows that a farmer will always find it profitable to accumulate skill over the life cycle, until the last period. A closer look at technology reveals that the marginal return of time investment is linear in the current level of skill. This, combined with the fact that the profit function $\pi(z, s)$ is linear in z, leads to the following lemma.

Lemma 1. *Optimal time investment is independent of initial skill draw*

Lemma 1 implies that the lifetime discounted income of a farmer is a linear function in *initial* skill type. For a worker, it is independent of skill type. Hence, the division of household members between occupations is characterized by a threshold skill level $\bar{z}$. Members with *initial* skill type above $\bar{z}$ will work as farmers, and those with skill type below $\bar{z}$ will become workers. Each period, household income consists of farm profit, labor income, and land rental income. The household head then divides income between consumption and saving. Formally, the household problem is

$$\max_{\{c_{a,\tau},c_{n,\tau},s_\tau,a_\tau,\bar{z}\}} : \sum_{\tau=1}^{T} \beta^{\tau-1} U(c_{a,\tau}, c_{n,\tau})$$

$$s.t: \; pc_{a,\tau} + c_{n,\tau} + a_{\tau+1} = a_\tau R + Y_\tau,$$

where R is the return on saving and $Y_\tau = \int_{\bar{z}}^{\infty} \pi(z, s_\tau) dG(z) + w \cdot G(\bar{z}) + q \cdot \bar{L}/T$ is the period household income. Households are assumed to born with zero assets, and do not die in debt, i.e., $a_0 = 0, a_{T+1} > 0$.

1.2.5 Equilibrium

I focus on stationary equilibria. A stationary competitive equilibrium is defined as *a collection of prices* (w, p, q, R), *consumption and investment allocations* $\{c_{a,\tau}, c_{n,\tau}, s_\tau, a_\tau\}_{\tau=1}^{T}$, *a skill threshold* $\bar{z}$, *factor demand* $h_a(z,s), \ell(z,s), H_n$ *such that: (1) given prices,* $\{c_{a,\tau}, c_{n,\tau}, s_\tau, a_\tau\}_{\tau=1}^{T}$ *and* $\bar{z}$ *solve household's maximization problem; (2) given prices,* $h_a(z,s), \ell(z,s)$ *solve farmer's profit maximization, and* H_n *solve non-agricultural firm's profit maximization; (3) all markets clear.*

To solve for equilibrium, it is convenient to first define the following variable.

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

$\{x_\tau\}_{\tau=1}^{T}$ summarize the level of skill at time τ relative to the initial draw. Since $\{x_\tau\}_{\tau=1}^{T}$ is independent of skill levels, it allows convenient characterization of aggregate variables. To solve the model, I begin by solving price of agricultural good (p) and land rental (q). Equation (1.4) below states the indifference condition for the marginal farmer with skill type $\bar{z}$. Specifically, it states that the marginal farmer earns the same discounted lifetime income as a farmer or as a worker. Equation (1.5) below states the land market clearing condition, which utilizes the fact that land demand is linear in skill input.

$$\pi(\bar{z}) \cdot \sum_{t=1}^{T} \{x_t \cdot (1 - s_t) \cdot R^{1-t}\} = \sum_{t=1}^{T} \{w \cdot R^{1-t}\}, \tag{1.4}$$

$$\int_{\bar{z}} \ell(z) dG(z) \cdot \sum_{t=1}^{T} \{x_t \cdot (1 - s_t)\} = \bar{L}. \tag{1.5}$$

Dividing (1.4) by (1.5) yields an expression for the rental price of land:

$$q = \left[\frac{\sum_{t=1}^{T} \{x_t \cdot (1 - s_t)\}}{\sum_{t=1}^{T} \{x_t \cdot (1 - s_t) \cdot R^{1-t}\}} \right] \cdot \left[\frac{\gamma \cdot (1 - \alpha) \cdot \left(\sum_{t=1}^{T} \{w \cdot R^{1-t}\} \right)}{(1 - \gamma) \cdot \bar{L}} \right] \cdot \frac{\int_{\bar{z}} z dG(z)}{\bar{z}}. \tag{1.6}$$

Substituting (1.6) into (1.5) yields the relative price of agricultural good:

$$p = \left[\frac{\sum_{t=1}^{T} \{w \cdot R^{1-t}\}}{\bar{z} \cdot (1 - \gamma) \cdot \sum_{t=1}^{T} \{x_t \cdot (1 - s_t) \cdot R^{1-t}\}} \right]^{1-\gamma} \cdot \left(\gamma \left(\frac{\alpha}{w} \right)^{\alpha} \left(\frac{1 - \alpha}{q} \right)^{1-\alpha} \right)^{-\gamma} \cdot \frac{1}{A}. \tag{1.7}$$

Solving for optimal consumption bundles and aggregating over generations yields the aggregate demand of two consumption goods:

$$C_a = \sum_{t=1}^{T} c_{at} = \left[\sum_{t=1}^{T} (\beta R)^{t-1} \right] \cdot \left[\frac{Y - p \cdot \bar{a} \sum_{t=1}^{T} R^{1-t}}{\sum_{t=1}^{T} \beta^{t-1}} \right] \cdot \frac{\eta}{p} + T \cdot \bar{a}, \tag{1.8}$$

$$C_n = \sum_{t=1}^{T} c_{nt} = \left[\sum_{t=1}^{T} (\beta R)^{t-1} \right] \cdot \left[\frac{Y - p \cdot \bar{a} \sum_{t=1}^{T} R^{1-t}}{\sum_{t=1}^{T} \beta^{t-1}} \right] \cdot (1 - \eta), \tag{1.9}$$

where

$$Y = wG(\bar{z}) \sum_{\tau=1}^{T} R^{1-\tau} + \sum_{\tau=1}^{T} x_\tau (1 - s_\tau) R^{1-\tau} \int_{\bar{z}} \pi(z) dG(z) + q\bar{L}/T \sum_{\tau=1}^{T} R^{1-\tau}$$

is the discounted income of a household. Given the threshold skill type $\bar{z}$, the measure of workers within a household is $G(\bar{z})$. Hence, the total measure of worker in the economy is simply $T \cdot G(\bar{z})$. The aggregate demand of workers in agriculture is given by

$$H_a = \left[\sum_{\tau=1}^{T} x_\tau (1 - s_\tau)\right] \cdot \int_{\bar{z}} h_a(z) dG(z).$$

Imposing labor market clearing, the measure of workers in the nonagricultural sector is $H_n = T \cdot G(\bar{z}) - H_a$. The aggregate output in agriculture and non-agriculture are then given by

$$Y_a = \left[\sum_{\tau=1}^{T} x_\tau (1 - s_\tau)\right] \cdot \int_{\bar{z}} y_a(z) dG(z),$$

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

Goods market clearing conditions require $C_a = Y_a, C_n = Y_n$. Loan market clears by Walras' law.

Finally the linear technology in non-agriculture implies $w = A$. Hence, the two goods market clearing conditions constitute two equations with two unknowns $(\bar{z}, R)$ that can be solved numerically. Once the cut-off skill and interest rates are known, rest of the equilibrium variables can be recovered easily.

1.2.6 Farm Size and Agricultural Productivity

Recall that this paper is about explaining two stylized facts: 1) productivity differences in agriculture are larger than those in non-agriculture; 2) mean farm size increases with income level. Before moving to the quantitative results, I discuss how the simple model constructed so far can deliver these two implications simultaneously.

First note that total output in agriculture can be written as

$$Y_a = A \cdot \left(\sum_{\tau=1}^{T} x_\tau (1 - s_\tau) \int_{\bar{z}} z dG(z) \right)^{1-\gamma} \left(H_a^\alpha \bar{L}^{1-\alpha} \right)^\gamma .$$

The measure of the labor force in agriculture is $T[1 - G(\bar{z})] + H_a$. It then follows that labor productivity in agriculture is

$$\begin{aligned} yala &= \frac{Y_a}{T[1 - G(\bar{z})] + H_a} \\ &= \underbrace{A}_{TFP} \cdot \underbrace{\left(\sum_{\tau=1}^{T} x_\tau (1 - s_\tau)/T \right)^{1-\gamma}}_{\text{Skill Growth}} \cdot \underbrace{\left(E(z|z > \bar{z}) \right)^{1-\gamma}}_{\text{Occupation Choice}} \cdot \Pi, \end{aligned} \tag{1.10}$$

where

$$\Pi = \frac{\left(\bar{L}\right)^{(1-\alpha)\gamma} \left(H_a\right)^{\alpha\gamma} \left(T[1 - G(\bar{z})]\right)^{1-\gamma}}{T[1 - G(\bar{z})] + H_a}$$

Equation (1.10) highlights two important forces that affect labor productivity in agriculture, other than exogenous TFP. The first one, labeled "Skill Growth", summarizes the increase in productivity due to skill accumulation. The second one, labeled "Occupation Choice", summarizes the average *initial* skill of farmers. Other things equal, labor productivity in agriculture is lower if farmers on average have low initial skill, or invest very little to improve productivity over the life cycle.

How does skill accumulation and occupation choice vary with exogenous TFP? This paper argues that when aggregate TFP is low, more individuals become farmers even though they have low initial skill draws. Meanwhile, farmers invest very little to improve their skill over the life cycle. These equilibrium allocations are direct implications of non-homothetic preferences. When TFP is low, on the one hand, a large fraction of income is spent on agricultural good; on the other hand, the technology for producing agricultural good is inferior. The price of agricultural good (relative to non-agricultural good) is hence higher. More individuals choose the sector with high price and the marginal farmer is moving further down the skill distribution. The result is a larger pool of farmers with lower average initial skill.

Over the life cycle, individuals save less when TFP is low. This is because the inter-temporal elasticity of substitution is low when income is low. The marginal utility from a unit of consumption when is much higher precisely when income is low. Hence, the marginal cost of skill accumulation is much higher in a low TFP economy, rendering such investment less preferable.

Low aggregate TFP not only directly decreases labor productivity in agriculture, but also does so indirectly through reducing the average initial skill of farmers and limiting skill accumulation. Note that TFP in this economy also maps into output per worker in non-agriculture because of the linear technology in that sector. Hence, the model is able to generate larger productivity differences in agriculture than in non-agriculture.

In the model economy, a farm is essentially consists of a farmer and a piece of land that she rents. Mean farm size (MFS) is simply the ratio of land to the measure of farmers, i.e., MFS $= \frac{\bar{L}}{T[(1-G(\bar{z})]}$. As discussed above, more individuals choose farming in a low TFP economy. Equivalently, the threshold skill type $\bar{z}$ is lower in a low TFP economy. Given the same amount of land, it is straightforward to see that mean farm size increases with the level of income, as in the data.

1.3 Quantitative Analysis

I calibrate the model to the U.S. In particular, the model reproduces the size distribution of farms and time allocation of farmers in the U.S. I explore the quantitative predictions of the model using a sample of 50 countries. TFP and land endowment are exogenous to the model and are directly inferred from the data. The model speaks to labor productivity in agriculture, the size distribution of farms, the allocation of labor between sectors, and the relative price of agricultural good. These implications are compared with those in the data.

1.3.1 Calibration

I begin with parameters whose values can be chosen without solving the model. I set the model period to be 10 years. Individuals start at the age 25, and live for 5 model periods. Hence, T = 5. Assuming an annual discount rate of 0.96, I set $\beta = (0.96)^{10}$. For the U.S., TFP is normalized to be 1.[7] Arable land per worker in the U.S. is 1.62 hectares. Correspondingly I set $\bar{L} = 1.62$. In the agriculture technology, γ dictates the income share accruing to farmers and $\alpha\gamma$ is income share accruing to labor. I use value added data from U.S. census of agriculture. Over the period 1980-1999, the average share of agricultural output accruing to farm operators

[7] In a strict sense, this normalization is not free because of the subsistence term in the utility function. However, the model is homogenous with respect to ($\bar{a}$, A). Hence, as long as $\bar{a}$ is chosen correspondingly, the model predictions does not change with different values of A for the US.

is 40 percent. Hence, I set $1-\gamma=0.6$. Then α is chosen such that labor share ($\alpha\gamma$) is consistent with estimates in Hayami and Ruttan (1970).[8]

The distribution of initial skill type is assumed to take a log-normal form with mean μ and standard deviation σ. Together with two preferences parameter ($\eta, \bar{a}$) and skill accumulation technology parameter (θ), there are five parameters that are chosen simultaneously to match the following moments in U.S. data. From the World Development Indicator, agriculture employs 3 percent of the labor force. I also target a long run employment share of 0.5 percent in agriculture.[9] This corresponds to the asymptotic agricultural employment share when the subsistence consumption share of income is effectively zero.

Within the model, farmers divide time between production and skill accumulation. However, direct observation on the time split between these two activities are not available in the data. Instead, I use cross-sectional distribution of hours of farmer operators, which are available from the Census of Agriculture. Specifically, I calculate the number of hours supplied by farm operators in five age groups: 25-34, 35-44, 45-54, 55-64, 65+. These numbers give rise to a age distribution of hours of farm operators. The corresponding distribution in the model is given by $\frac{1-s_i}{\sum_{i=1}^{T} 1-s_i}$. This is because farmers of the same age allocate time between production and skill

[8]Existing estimates of the span-of-control parameter are mostly for manufacturing or the aggregate economy, e.g., Atkeson and Kehoe (2005), Guner, Ventura, and Yi (2008), Restuccia and Rogerson (2008), Gollin (2008), and the value typically falls in the ballpark of 0.85. To my best knowledge, there is no consensus on the range of this parameter for agriculture. A value of 0.6 is nevertheless a conservative choice as a higher γ tends to strengthen the quantitative results.

[9]A similar strategy is used in Restuccia, Yang, and Zhu (2008).

accumulation in an identical way. I target the the fraction of hours supplied by farmer aged 35-45. Finally, I target the first two moments of the empirical size distribution of farms, which are available from census of agriculture. Table 2.1 offers a summary of parameter values and how they are selected.

Table 1.2: Parameter description, value, and source of Identification

Parameter	Description	Value	Source
A	TFP	1	Normalization
T	Life cycle	5	Born 25, die 75
β	Discount Rate	$(0.96)^{10}$	Common value
$\bar{L}$	Land endowment	1.62	Arable land per worker
γ	Span-of-control	0.6	Income share, farm operator
α	Labor share, agriculture	0.8	Hayami and Ruttan (1970)
η	Preferences	0.01	Long run labor share, agr.
$\bar{a}$	Subsistence	0.2	Current labor share, agr.
θ	Time elasticity	0.33	Hour distribution of farmers
μ	Skill distribution, mean	-2.45	Farm size distribution, mean
σ	Skill distribution, stdv	4.16	Farm size distribution, stdv

Figure A.1 plots the calibrated size distribution against data. The match is quite good even though I only target the first two moments of the distribution. In addition, as depicted in Figure A.2, the model also implies a land distribution that fits the data very well, even though it is not targeted. Table A.2 presents the age distribution of hours for farm operators. Although in the calibration I only target the hour of farm operators aged 35-44, the model actually matches the entire distribution pretty well.

1.3.2 Results

I explore the quantitative implication of the model using a sample of 50 countries, with a wide range in the degree of development. GDP per worker ranges from less than 700 (Ethiopia) to more than 30,000 (United States) in 1985 international dollars. Countries differ in their total factor productivity (A) and land endowment ($\bar{L}$), and are otherwise identical. In particular, countries face the same distribution of skill types *ex-ante*. Land per worker is directly available from data. Utilizing the linear technology in non-agriculture, I infer TFP of country i as $A_i = \frac{ynln_i}{ynln_{us}}$, where $ynln_i$ is PPP non-agricultural GDP per worker of country i. Non-agricultural output per worker is directly available from Restuccia, Yang, and Zhu (2008).

I first look at model's prediction on agricultural productivity. To ease comparison with data, I compute two statistics. Following Caselli (2005), I first compute the ratio of log-variance of model generated productivity series to that of the data. This ratio is 0.45, suggesting that the model explains about 45% of the cross-country variation in agriculture output per worker. As an alternative, I perform OLS regression of model productivity series on their data counterpart. The R^2 is 0.49. Figure 1.4

plots agriculture output per worker (relative to the U.S.) in the data on the horizonal axis, and those in the model on the vertical axis. The model does pretty well explaining productivity differences across countries. A visual outlier is Nepal, for which the model over-predicts its agricultural productivity by a lot. The reason is that Nepal, despite a very high employment share in agriculture, has a very productive non-agricultural sector. This maps into high TFP, and leads to a counterfactually high productivity in agriculture.

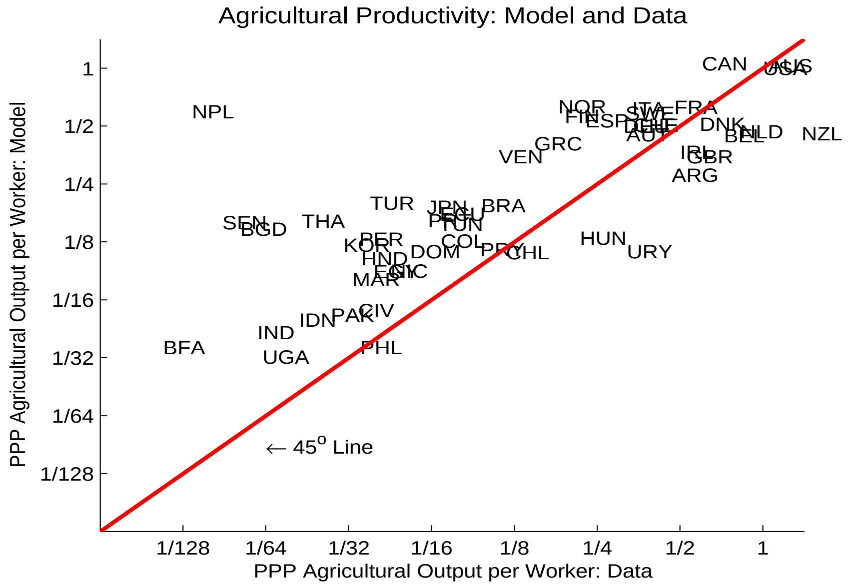

Figure 1.4: Output per worker in agriculture: model and data

Low agricultural productivity is mainly due to low total factor productivity, as opposed to small land endowment. Consider, for concreteness, the poorest country in the sample (Burkina Faso). Relative to the U.S., Burkina Faso is 4.8 times less productive overall and has 2.6 times less land per worker. Imagine that Burkina Faso has the U.S. land endowment, but its own TFP. This can not help Burkina Faso catch up with US in agricultural productivity - the gap shrinks from a factor 28 to 22. In contrast, if Burkina Faso has the U.S. level of TFP and its own land endowment, its productivity in agriculture is increased big time - the gap shrinks to merely a factor of 1.2. Productivity differences across countries are mainly a story of TFP differences. This is true not only at the aggregate level as highlighted in Prescott (1998), Hall and Jones (1999) and Caselli (2005), but also in agriculture.[10]

The model generates endogenously a size distribution of farms. There is a unique mapping between the *equilibrium* distribution of skills and the size distribution of farms. In an economy with low TFP, the average farmers possess lower initial skill and invest less in skill accumulation. It follows that in poor countries, average farm size is smaller; and small farms constitute a larger share of all farms. Figure 1.5 plots on the horizontal axis mean farm size in the data, and on the vertical those in the model. The model successfully captures the increase in mean farm size with income level as in the data. In the Appendix, the size distributions of some selected countries are plotted against their empirical counterparts. In fact, the model does even better,i.e., the model reproduces the empirical farm size distributions fairly well. In appendix, I plot the endogenous size distributions along with their empirical counterparts. For countries in different levels of development, the endogenous size

[10]Using measures at the sector level, Caselli (2005) concludes that TFP differences are larger in agriculture than in the aggregate.

distributions closely resemble the empirical ones. This feature of the model offers discipline on the key hypothesis of the paper, namely, skill differences are important sources of labor productivity differences in agriculture.

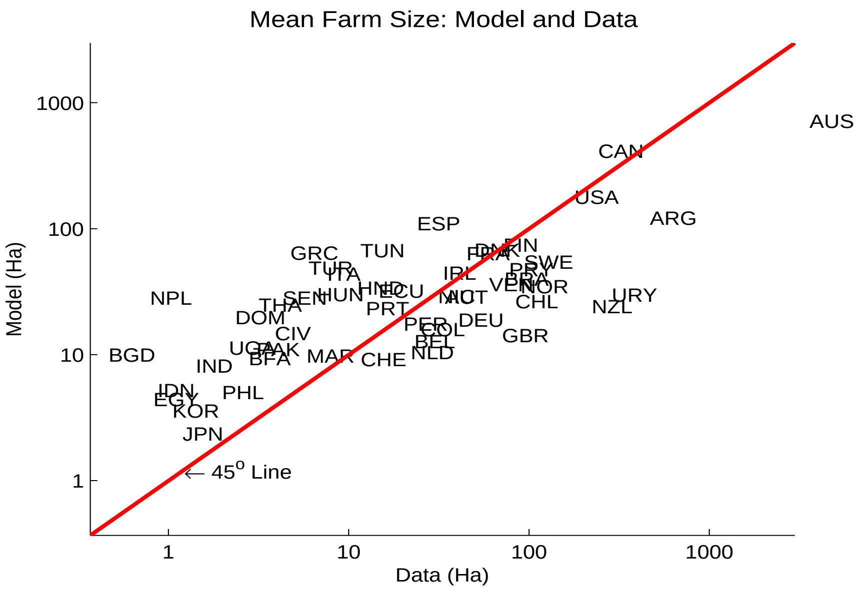

Figure 1.5: Mean farm size: model and data

1.3.3 Other Implications

I explore other implications of the model here. In addition to low productivity, agriculture absorbs most of the labor force in poor countries. As income rises, labor moves from agriculture to the other sectors of the economy. This process is known as “structural change”. The model is able to capture the decrease in the share employment in agriculture as income rises. This aspect of the model is depicted in Figure

1.6. It is notable that, for low income countries, the model generally under-predicts the share of employment in agriculture. This suggests other forces might be at work, that are not captured by differences in aggregate TFP. In the current environment, labor is perfectly mobile. This might be a poor description of the labor market in developing countries. Barriers to labor movement, especially those restricting individuals moving from rural to urban sectors, are known to prevail in developing countries. A frequently cited example is the *hukou* system in China. Quantitatively, Restuccia, Yang, and Zhu (2008) show that these barriers are important for understanding cross-country differences in productivity and labor allocation.

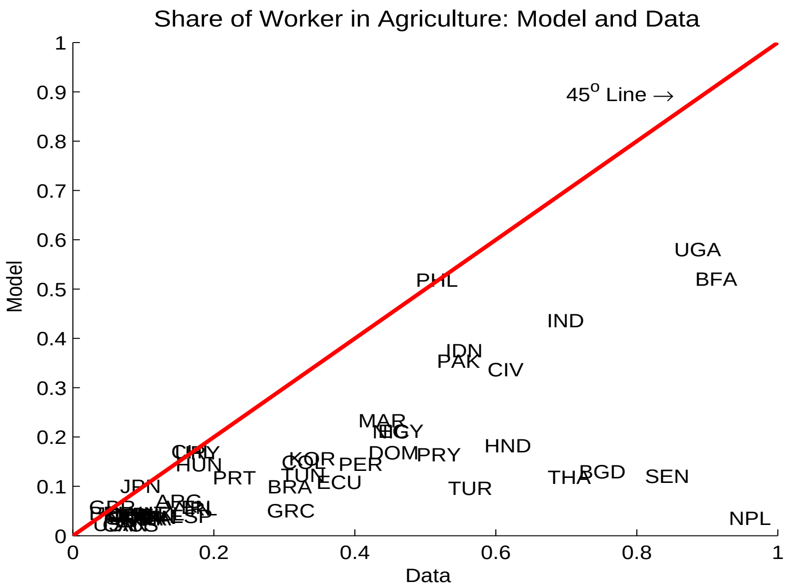

Figure 1.6: Share of employment in agriculture: model and data

In addition to labor, agriculture's share of total output declines as income rises

- a macroeconomic implication of Engel's Law. The model is consistent with this empirical regularity as well. Agriculture' share of GDP falls from 70% in the poorest 10 percent of countries to less than 10 percent in the richest 10 percent of countries. In the data, the value is 30% and 3%, respectively. One possible explanation is that the model overshoots the relative price of agricultural output, resulting in a higher agriculture share of GDP when measured at domestic prices. Using data from the International Comparison Program (ICP) of the World Bank, I compute the relative price between "agricultural consumption" and "nonagricultural consumption" for all available countries.[11] I find that the relative price is in fact higher in poor countries than that in rich countries - a fact that the model is consistent with. Quantitatively, the relative price is around 2.3 times higher in the 10th percentile country, compared to the 90th percentile country. In the model, this relative price ratio is 2.8, which is roughly in line with the data.

1.4 Conclusion

Agriculture in developing countries exhibits two salient features. First, it is unproductive. Second, farms are predominantly small. The exact reverse were found in developed countries. This paper presents an explanation of these stylized facts. The model features endogenous skill accumulation in a life-cycle version of Lucas's span-of-control model. I use the calibrated model to evaluate the role economy-wide

[11] "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 Lagakos and Waugh (2010)

efficiency has on agricultural productivity. I found that, because of the interaction between endogenous skill accumulation of farmers and economy-wide efficiency, the model generates much larger differences in agricultural productivity for a given order of differences in economy-wide efficiency. Quantitatively, the model is able to account for 50 percent of the cross-country differences in agricultural productivity, while matching the data in terms of productivity outside agriculture. Moreover, the model successfully accounts for the differences in the size distribution of farms and productivity growth of farmers observed in the data between developing and developed countries.

The agricultural sector characterized in this paper is "poor but efficient", as articulated in Schultz (1964). In this aspect, this paper complements existing research that focus on agriculture-specific distortions as explanations of low productivity in agriculture of developing countries. Nonetheless, distortions such as barriers to sectoral labor movements, and implicit government taxation on agriculture as discussed in Krueger, Schiff, and Valdes (1988) and Anderson (2009), might be key to understand the coexistence of high employment and low productivity in agriculture of developing countries.

CHAPTER 2
SKILL ACCUMULATION AND SECTORAL PRODUCTIVITY DIFFERENCES ACROSS COUNTRIES

2.1 Introduction

Between rich and poor countries, differences in output per worker in agriculture are twice as large as the differences in aggregate GDP per worker, and ten times larger than the differences in output per worker in non-agriculture (Caselli (2005), Restuccia, Yang, and Zhu (2008)). Even after accounting for physical capital, cross-country productivity differences in agriculture remain much larger than those in the aggregate and in non-agriculture.[1] Because agriculture employs most of the labor force in poor countries, much of the observed differences in aggregate income per worker can be attributed to differences in output per worker in agriculture. Consequently, understanding labor productivity differences in agriculture and non-agriculture is key to understanding world income inequality.

This paper presents a model that accounts for sectoral productivity differences across countries. The model features skill accumulation in a two-sector, life-cycle model of self-selection. Aggregate TFP interacts with individual's occupational choices and skill accumulation decisions. These interactions generate implications for the quality of labor in each sector. Labor quality, together with TFP, produces sectoral labor productivity differences across countries.

My model builds on Lagakos and Waugh (2010). The model economy is pop-

[1] See appendix B.1 for calculating capital stock at the sector level.

ulated by a large number of individuals who live for finite periods. When born, individuals draw a pair of skills from an exogenous distribution, which determine their initial productivity in agriculture and non-agriculture. Conditional on the draws, individuals make an irreversible decision whether to become farmers or workers. Each occupation utilizes only one component of an individual's skills. Farmers have access to a Lucas's span-of-control technology while workers work for a wage. While on the job, both farmers and workers can accumulate skills specific to their occupations, and increase future productivity. Accumulating skills requires time away from production, and reduces current period income. Span-of-control in agriculture and on-the-job skill accumulation are two key features that separate this paper from Lagakos and Waugh (2010).

In equilibrium, the labor force in each sector comprises a cross-sectional distribution of individuals with different skills and of different ages. These distributions depend on the level of TFP. In an economy with low TFP, the labor force comprises many farmers with poor agricultural skill, and few workers who highly specialize in non-agricultural production. Importantly, the poor skill of farmers is a joint result of low *initial* skill and low investment in skill accumulation. First, low TFP dictates that more individuals, including those with low initial agricultural skill, produce in agriculture to meet the minimum consumption requirement. Second, low level1 of TFP reduces skill accumulation through an income effect. Because of the minimum consumption constraint, diverting an extra unit of time from production to skill accumulation is associated with more loss in utility precisely when TFP (and, hence, income) is low.

The model is calibrated to match both macroeconomic statistics and cross-sectional features of the labor force in the U.S. I make parametric assumptions on the distribution of initial skills, and posit a skill accumulation function similar to that in Ben-Porath (1967). The relevant parameters are chosen such that the model matches the cross-sectional distribution of earnings in agriculture and non-agriculture, as well as the age-earnings profile of farm operators and non-agriculture workers in the U.S.

The central question of interest is whether the model can reproduce the observed cross-country productivity differences in agriculture and in non-agriculture. For this purpose, countries are assumed to be identical except for their levels of aggregate TFP. For each country, its level of TFP is chosen such that *aggregate* real GDP per worker in the model exactly matches that in the data. The model's predictions of output per worker in agriculture and non-agriculture are then compared to the data.

Between the 90th percentile country and the 10th percentile country in the world income distribution, there is a factor of 22 difference in aggregate GDP per worker, which the model matches by construction. The model generates a difference in agricultural productivity that is 1.8 times larger than the difference in aggregate GDP per worker, and 5.7 times larger than the difference in non-agricultural productivity. This ratio is 2 and 10, respectively, in the data.[2]

[2]With externality in skill accumulation, the model can account for most of the labor productivity differences in agriculture and non-agriculture. See Section 5 for a detailed discussion.

Quantitatively, the model is consistent with the data in other dimensions. First, the model predicts that 75 percent of the labor force are farmers in the 10th percentile country, which is close to the 80 percent observed in the data. As income rises, the share of farmers in the labor force declines to less than 3 percent in the 90th percentile country, both in the model and in the data.

Second, using farm size as a proxy for productivity, I compute productivity growth of a farmer between the age 25 and 45 in a poor country, Nepal, and in a rich country, United States. The data suggests that the growth of productivity is 19 percent lower in Nepal, relative to that in the U.S., which is close to the 13 percent predicted by the model.[3]

Third, the model explains the prevalence of small farms in low income countries. Consider the poorest 10 percent of the countries in the sample. The model generates endogenously a farm size distribution that has the following features: 1) 89 percent of all farms are below 5 hectares, and only 2.5 percent exceed 10 hectares; 2) 84 percent of farm land is in farms below 5 hectares, and only 5.1 percent is in farms above 10 hectares. These statistics closely resemble those in the data. The reason is that farms start small and stay small in poor countries due to limited skill accumulation by farmers. This explanation contrasts with that in Adamopoulos and Restuccia (2011). They suggest that farm level distortions that prevent large farms

[3]The productivity growth of a U.S. farmer between age 25 and 45 has been increasing over time as well. In 1964, a farmer's productivity grew by as little as 10 percent between age 25 and 45. The productivity gain increased to 40 percent in 1982, and 60 percent in 2007.

from operating at the optimal scale, is the reason why farms are small in poor countries.

This paper fits into a growing body of recent literature that develops *quantitative* explanations for cross-country productivity differences in agriculture and non-agriculture. Chanda and Dalgaard (2008) and Vollrath (2009) find that differences in factors of production cannot account for the differences in productivity. Gollin, Lagakos, and Waugh (2011) find that while part of the differences are due to measurement errors, a large gap remains after adjusting for such errors.[4] Previous work has focused on specific barriers. Examples are barrier to capital accumulation in Gollin, Parente, and Rogerson (2004), barrier to intermediate inputs in Restuccia, Yang, and Zhu (2008), distortions limiting farm size in Adamopoulos and Restuccia (2011), and high transportation costs in Adamopoulos (2011). This paper instead focuses on aggregate barriers such as low TFP, and their effects on the quality of labor in agriculture and non-agriculture. My approach complements that of Lagakos and Waugh (2010) by introducing skill accumulation into a Roy model of self-selection, and highlights the role of aggregate TFP.

The rest of the paper is organized as follows. Section 2 describes the model. Section 3 explains the calibration strategy. Section 4 presents the main results from the benchmark model. Section 5 extends the benchmark model to include externality, and discusses the implications. Section 6 concludes.

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[4]See also Herrendorf and Schoellman (2011) for an investigation on the productivity gap between agriculture and non-agriculture in the U.S. using state level data.

2.2 Model

Each date, a continuum (of mass one) individuals are born. Individuals live for T periods, and maximize discounted utility from consumption

$$\sum_{\tau=1}^{T} \beta^{\tau-1} U(c_{a,\tau}, c_{m,\tau}),$$

where c_a is an agriculture consumption good, and c_m is an non-agriculture consumption good. I adopt the following instantaneous utility function $U(c_a, c_m) = \eta log(c_a - \bar{a}) + (1-\eta) log(c_m)$. The parameter $\bar{a}$ is the minimum level of agriculture consumption that each individual must maintain. When $\bar{a} > 0$, two implications follow. First, expenditure on agriculture consumption as a share of income declines with income. Second, the inter-temporal elasticity of substitution in agriculture consumption is low when income is low.

Individuals are initially endowed with a pair of skills $(z_{a,1}, z_{m,1})$. These initial skills are *i.i.d* draws from a joint distribution $G(z_{a,1}, z_{m,1})$. Skill $z_{a,1}$ determines an individual's *initial* productivity in agriculture, and $z_{m,1}$ determines an individual's *initial* productivity in non-agriculture. At age 1, individuals choose to become either workers or farmers. Regardless of occupation, individuals are endowed with one unit of time in each period. A worker supplies her non-agricultural skill to the market in exchange for a wage. Each period, a worker decides the time allocation between market work and skill accumulation, and splits income between consumption and saving. A farmer produces output combining her agricultural skill and land rented from the market, and retains residual profits. A farmer's problem in each period is three-fold: the quantity of land to rent, time allocation between skill accumulation and production, and the division of profits between consumption and saving. Note that while the initial endowment of skill $(z_{a,1}, z_{m,1})$ is exogenous, skills at age $\tau > 1$, $(z_{a,\tau}, z_{m,\tau})$, are endogenous.

The economy is endowed with a fixed stock of land that is equal to L, which is equally owned by all individuals. There is no lifetime uncertainty or population growth. So population at any point in time is T. Hence, each individual owns $\bar{\ell} = L/T$ quantity of land.

There are competitive markets of land rental, two consumption goods, and inter-temporal loans.

2.2.1 Technology

2.2.1.1 Production

In non-agriculture, there is a representative firm that hires labor and produces output with the following technology:

$$Y_{m,t} = A \cdot H_{m,t}, \tag{2.1}$$

where A is total factor productivity (TFP), and $H_{m,t}$ is the composite of *skill weighted labor hours* supplied by non-agriculture workers of all ages at time t. Let $z_{m,\tau,t}$ denote the skill level of an age-τ worker, and $(1 - s_{\tau,t})$ her fraction of time allocated to production at time t. Given the set of age-τ workers at time t, $\Omega_{m,\tau,t}$, we have

$$H_{m,t} = \sum_{\tau=1}^{T} \left[\int_{j \in \Omega_{m,\tau,t}} z^j_{m,\tau,t}(1 - s^j_{\tau,t}) dG^j \right]. \tag{2.2}$$

Implicitly, skills of different workers are assumed to be perfect substitutes in production. As a result, there is a single wage rate per unit of skill-hour.

Each farmer has access to the following Lucas (1978) span-of-control technology

$$y_a = A \cdot (z_a(1-s))^{1-\gamma}\, \ell^{\gamma}, \tag{2.3}$$

where $z_a(1-s)$ is *skill weighted labor hours* allocated to production and ℓ is the quantity of land. TFP in agriculture is the same as that in non-agriculture, and is common to all farmers.

Individuals working in agriculture are self-employed farmers, or farm managers. Nobody works for wage in agriculture. In other words, hired labor is not an essential input in agricultural production. In the appendix, I document evidence supporting this specification. In a nutshell, I find that self-employment is a dominant form of employment in agriculture across all income levels.

2.2.1.2 Endogenous Skill Accumulation

Individuals can increase future productivity over the life cycle by allocating time to skill accumulation. Because of the sector-specificity of skill, individuals only accumulate skills specific to the sector they choose at the first date. The law of motion for skill from age τ to $\tau+1$ is given by

$$z_{i,\tau+1} = (1-\delta_{i,\tau})z_{i,\tau} + f(z_{i,\tau}, s_\tau) \quad i = \text{a, m}, \tag{2.4}$$

where $s_\tau \in [0,1]$ is the fraction of time allocated to skill accumulation, $\delta_{i,\tau}$ is the depreciation of skill from age τ to $\tau+1$. The skill production function, $f(z_{i,\tau}, s_\tau)$, has the following parametric form:

$$f(z_{i,\tau}, s_\tau) = z_{i,\tau}^{\phi_i} s_\tau^{\theta_i}.$$

This production function satisfies the following properties: $f(z_i, 0) = 0, f(0, s) = 0, f_s(z_i, 0) = \infty$. The first two properties imply that both skill and time are essential inputs in skill accumulation. The last property guarantees that accumulation of skills is always profitable given a positive (finite) price of skill. The parameters ϕ_i and θ_i control the relative importance of current skill and time in skill accumulation. Finally, I restrict $\theta_i < 1$ to ensure there are diminishing returns to investment.

Several remarks on the technologies are in order. First, individual skills are sector-specific, i.e., production in a sector requires only one type of skill. It is more appropriate to interpret these skills as representing knowledge or know-how that are unique to production in agriculture or non-agriculture. Examples of such skills are optimal combination of seed and fertilizer in crop production, or efficient ways of writing computer codes in software engineering. As such, it is less appropriate to interpret skill as summarizing one's intelligence, health, or general knowledge. Second, TFP is sector neutral. Hence, a priori agriculture is not assumed to be less productive than non-agriculture within a country.

Lastly, the skill accumulation process is the same as in Ben-Porath (1967), except that I do not have goods input in skill accumulation. It is now a standard result that when human capital production requires physical goods as an input, TFP has a stronger effect on the stock of human capital (Manuelli and Seshadri (2005), Erosa, Koreshkova, and Restuccia (2010)). The reason is that low TFP directly increases the price of human capital investment. In this paper, the *level* of TFP affects skill accumulation through an income effect. Three ingredients of the model are central to this result. First, individuals live finite periods. Second, there is no physical capital. Therefore, the interest rate in a stationary equilibrium is not pinned down by preference parameters, and, hence, can vary with the level of TFP. Third, individual preferences feature a minimum consumption constraint. When TFP (and, hence, income) is low, an extra unit of time diverted from production to skill accumulation is associated with higher utility loss in the current period. This renders skill investment more costly and individuals optimally reduce time allocated to skill accumulation.

2.2.2 Optimization

In the quantitative analysis, I focus on model implications in the steady state. To save on notation, I state the optimization problems in a stationary environment, where the price of agriculture consumption (p), rental price of land (q), rental price of skill-hour in non-agriculture (w), and gross interest rate (R) are all constant. These prices are expressed relative to the price of output in non-agriculture, which is used as the numeraire.

2.2.2.1 Individual

Consider the problem facing an individual with initial skills $(z_{a,1}, z_{m,1})$, who chooses to be a worker. She decides the sequence of time allocation $\{s_\tau\}$, consumption $\{c_{a,\tau}, c_{m,\tau}\}$, and asset holdings $\{a_\tau\}$ to maximize her life time utility. Her period income consists of wage income, return from asset holdings, and rental income from her share of land ($\bar{\ell}$). There is no borrowing constraint, as long as she does not die in debt. A worker's utility maximization problem is

$$\max \sum_{\tau=1}^{T} \beta^{\tau-1} U(c_{a,\tau}, c_{m,\tau}) \tag{2.5}$$

$$s.t: \ pc_{a,\tau} + c_{m,\tau} + a_{\tau+1} \leq wz_{m,\tau}(1-s_\tau) + a_\tau R + q\bar{\ell}$$

$$z_{m,\tau+1} = (1-\delta_{m,\tau})z_{m,\tau} + z_{m,\tau}^{\phi_m} {s_\tau}^{\theta_m}$$

$$0 \leq s_\tau \leq 1, a_{T+1} \geq 0, a_1 = 0$$

If the individual chooses to be a farmer, she has to decide the profit maximizing quantity of land each period in addition to consumption, saving, and skill accumulation decisions. Under complete markets, farmers's utility maximization problem can be separated from her profit maximization problem. The period profit of a farmer with skill z_a who allocates $(1-s)$ hours to production is given by

$$\pi(z_a, s) = \max_{\ell} : A \cdot p \cdot (z_a(1-s))^{1-\gamma} \ell^\gamma - q\ell,$$

It is straightforward to show that both the demand for land and period profit are linear in skill.

$$\pi(z_a, s) = (1-\gamma)z_a(1-s)(pA)^{\frac{1}{1-\gamma}} \left(\frac{\gamma}{q}\right)^{\frac{\gamma}{1-\gamma}},$$

$$\ell(z_a, s) = z_a(1-s) \cdot \left(\frac{pA\gamma}{q}\right)^{\frac{1}{1-\gamma}}.$$

The utility maximization problem of a farmer is

$$\max \sum_{\tau=1}^{T} \beta^{\tau-1} U(c_{a,\tau}, c_{m,\tau}) \tag{2.6}$$

$$\begin{aligned} s.t:\ & pc_{a,\tau} + c_{m,\tau} + a_{\tau+1} \leq \pi(z_{a,\tau}, s_\tau) + a_\tau R + q\bar{\ell} \\ & z_{a,\tau+1} = (1-\delta_{a,\tau}) z_{a,\tau} + z_{a,\tau}^{\phi_a} {s_\tau}^{\theta_a} \\ & 0 \leq s_\tau \leq 1, a_{T+1} \geq 0, a_1 = 0 \end{aligned}$$

Let $V_a(z_{a,1})$ denote the supremum associated with the maximization problem in (2.5), and $V_m(z_{m,1})$ denote the supremum associated with the maximization problem in (2.6). Because of the sector specificity of skills, the value of a worker does not depend on her agricultural skill, and the value of a farmer does not depend on her non-agricultural skill. At the first date, an individual's occupational choice problem is

$$\max_{\Upsilon=\{0,1\}} \quad \Upsilon V_a(z_{a,1}) + (1-\Upsilon) V_m(z_{m,1})$$

Correspondingly, the set of age-1 workers is given by $\Omega_{m,1} = \{j|\Upsilon^j = 0\}$, and the set of age-1 farmers is given by $\Omega_{a,1} = \{j|\Upsilon^j = 1\}$.

2.2.2.2 Firm

The representative firm in non-agriculture solves the following profit maximization problem

$$\max_{H_m} : AH_m - wH_m.$$

The first order condition implies a wage per unit of skill-hour $w = A$.

2.2.3 Equilibrium

A stationary competitive equilibrium is defined as as *a collection of prices (p, q, R, w), decision rules* $\{c_{a,\tau}, c_{m,\tau}, s_\tau, a_\tau\}_{\tau=1}^T$, $\ell(z_a, s)$, Υ, H_m *such that: (1) given prices,* $\{c_{a,\tau}, c_{m,\tau}, s_\tau, a_\tau\}_{\tau=1}^T$, *and* Υ *solve individuals' occupational choice problem, and* $\ell(z_a, s)$ *solves farmers' profit maximization problem; (2)* H_m *solves the non-agriculture firm's profit maximization problem; and (3) markets clear:*

$$\sum_{\tau=1}^{T}\left[\int_{j\in\Omega_{a,\tau}} y_{a,\tau}^j dG^j\right] = \sum_{\tau=1}^{T}\int c_{a,\tau}^j dG^j,$$

$$A \cdot H_m = \sum_{\tau=1}^{T}\int c_{m,\tau}^j dG^j,$$

$$\sum_{\tau=1}^{T}\left[\int_{j\in\Omega_{m,\tau}} z_{m,\tau}^j (1-s_\tau^j) dG^j\right] = H_m,$$

$$\sum_{\tau=1}^{T}\left[\int_{j\in\Omega_{a,\tau}} \ell(z_{a,\tau}^j, {s_\tau}^j) dG^j\right] = L.$$

Lemma 2. *If* $\phi_a = \phi_m = 1$, *then time investment over the life cycle is independent of initial skill.*

Lemma 1 implies a common slope of the age-earnings profile for all individuals working in the same sector. Between sectors, the slope differs up to elasticity of time in skill accumulation and depreciation. Moreover, the cross-sectional average of skill within a sector can be conveniently decomposed into two orthogonal components. One summarizes the average *initial* skill within a sector and the other one captures the growth of skill over time. I exploit this feature in Section 4.

2.2.4 TFP and Skill Accumulation in a Two-Period Model

The interaction between TFP and skill accumulation can be most clearly seen in a simplified two-period model. Consider the case of a farmer with initial agricultural skill z_a. In a stationary equilibrium, her skill accumulation problem is

$$\max_{s_a}: \quad z_a(1-s_a) + R^{-1}\left[(1-\delta_a)z_a + z_a^{\phi_a} s_a^{\theta_a}\right]$$

Assume that $\phi_a = \phi_m = 1$, then the optimal time investment is given by

$$s_a^* = \left(\frac{\theta_a}{R}\right)^{1/(1-\theta_a)}.$$

The sum of skill weighted labor hours in production is $z_a \cdot [2 - \delta_a + s_a^{*\theta_a} - s_a^*]$.[5] The increase in output generated through skill accumulation is captured by

$$\Lambda_a = \left(\frac{\theta_a}{R}\right)^{\theta_a/(1-\theta_a)} - \left(\frac{\theta_a}{R}\right)^{1/(1-\theta_a)}.$$

At the heart of this paper is that Λ_a increases with the level of total factor productivity. To see this, I first state two equilibrium conditions without proving. First, gross interest rate must exceed the discount rate in equilibrium, i.e., $R > 1/\beta > 1$. Second, because of the minimum consumption constraint, individuals have stronger motives to borrow and finance consumption in the first period when TFP is low. As a result, equilibrium interest is a decreasing function of TFP, i.e., $\frac{\partial R}{\partial A} < 0$. Differentiating Λ_a

[5] Obviously it is not optimal to allocate any time to skill accumulation in the second period.

with respect to TFP yields

$$\begin{aligned}\frac{\partial \Lambda_a}{\partial A} &= \frac{\partial \Lambda_a}{\partial R}\frac{\partial R}{\partial A} \\ &= \frac{1}{1-\theta_a}\left[R^{\frac{2-\theta_a}{\theta_a-1}}\theta_a^{\frac{1}{1-\theta_a}} - \theta_a R^{\frac{1}{\theta_a-1}}\theta_a^{\frac{\theta_a}{1-\theta_a}}\right]\frac{\partial R}{\partial A} \\ &= \left(\frac{1}{1-\theta_a}\right)\theta_a^{\frac{1}{1-\theta_a}}\left[R^{\frac{2-\theta_a}{\theta_a-1}} - R^{\frac{1}{\theta_a-1}}\right]\frac{\partial R}{\partial A} > 0. \end{aligned} \tag{2.7}$$

The last inequality follows from the assumption $0 < \theta_a < 1$ and the equilibrium condition $R > 1$.

2.3 Calibration

I calibrate the model to match the U.S. macroeconomic statistics and cross-sectional features of the labor force in agriculture and non-agriculture. I first describe a set of parameters that are either standard in the literature or whose values can be determined without solving the model. The values of the remaining parameters are chosen simultaneously by solving the model.

A model period is equal to 10 calendar years. Individuals start at the age of 25 and live 5 model periods. Discount rate $\beta = (0.96)^{10}$. The level of TFP for the U.S. is normalized to be 1. Herrendorf and Valentinyi (2005) estimate γ, the income share of land in agriculture, to be between 11% and 18%. In an effort to make results conservative, I set $\gamma = 0.11$.

I assume the marginal distributions of $G(z_{a,1}, z_{m,1})$ are Fréchet. However, I do not assume any correlation between the $z_{a,1}$ and $z_{m,1}$, i.e., $G(z_{a,1}, z_{m,1}) = G(z_{a,1}) \times$

$G(z_{m,1})$, where

$$G(z_{i,1}) = exp(-z_{i,1}^{-\lambda_i})$$

is the cumulative Fr$\acute{e}$chet distribution. The parameter λ_i controls the dispersion of initial skill in sector i for a given age group. The dispersion of earnings across age groups within a sector, however, depends both on the value of λ_i and the accumulation of skill over time. A smaller λ_i in general increases the dispersion of earnings, but more so with skill accumulation.

In the benchmark, I restrict $\phi_a = \phi_m = 1$. Instead of having a different depreciation rate for each age, I assume the following

$$\delta_i = \begin{cases} \delta_i^1 & \text{if } \tau <= 3 \\ \\ \delta_i^2 & \text{if } \tau > 3 \end{cases}$$

with $0 < \delta_i^1 < \delta_i^2 < 1$.

I am left with 11 parameters $(\lambda_a, \lambda_m, \theta_a, \theta_m, \delta_{a1}, \delta_{a2}, \delta_{m1}, \delta_{m2}, \eta, \bar{a}, L)$ to be chosen simultaneously to match the following targets: dispersion of earnings in agriculture and non-agriculture, ratio of mean earnings between farmers and non-agriculture workers, age-earnings profile of farmers and non-agriculture workers, the share of farmers in the labor force, the share of income on minimum agriculture consumption, and mean farm size.

I use cross-sectional data from the 2007 Current Population Survey (CPS). My sample includes individuals 25-65 with non-missing income and hours. Observations with weekly hours less than 35 or annual hours less than 1750 are excluded. I calculate earnings as the sum of wage and salary income, farm income and business income. Observations with earnings less than federal minimum wage are also dropped. Observations are then grouped into agriculture and non-agriculture based on their assigned occupation codes. See appendix A.1 for a detailed discussion of mapping occupations to sectors. The standard deviation of log normalized hourly earnings in agriculture is 0.48. In non-agriculture, it is 0.58. The mean earnings in agriculture is 69 percent of that in non-agriculture.

I construct the age-earnings profile in non-agriculture using the cross-sectional data from 2007 CPS. For agriculture, I use farm operator balance sheet data from 2007 Census of Agriculture. The variation in operator income over time is a more accurate measure of the changes in a farmer's endogenous skill. Changes in farmers' earnings in CPS, on the other hand, might reflect variations in off-farm employment and other business income. Government payments are not in the model. Correspondingly, I calculate farm operator income net of government payments.

I calculate the share of farmers in the labor force to be 1.74 percent.[6] The minimum consumption parameter is chosen such that a country with 7.5 percent of U.S. per capita GDP spends 34 percent of its income to meet the minimum consumption requirements.[7] The mean farm size in the U.S. is 169 hectares. Note that matching

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[6]The share of employment in agriculture in the U.S. is 2.9 percent. In 2007 CPS, 60 percent of the agriculture labor force are farmers, ranchers, and farm/ranch managers. Therefore, the share of farmers in the labor force is 1.74 percent.

[7]The same strategy is used in Lagakos and Waugh (2010). This evidence is based on studies of India. See Atkeson and Ogaki (1996), Rosenzweig and Wolpin (1993).

the mean farm size and the share of farmers in the labor force implies $L = 14.7$.[8]

Panel A of Table 2.1 summarizes the values of parameters that are determined without solving the model. Panel B lists the jointly calibrated parameters, and the corresponding targets to match.

The calibrated model is able to match the targets well. Figure B.5 plots the aggregate earnings distribution from the model, along with those in the data. Figure B.6 and Figure B.7 plots the distribution in agriculture and non-agriculture, respectively. While the parameters are calibrated to match only the dispersion of earnings, the model actually captures the earnings distributions fairly well. The model also generates an mean earnings ratio between agriculture and non-agriculture that is equal to 0.69. Figure B.8 and Figure B.9 demonstrates that the calibrated model matches the age-earnings profile in each sector very well.

Although not targeted, the implied size distribution of farms from the model captures two features of U.S. data: large farms (>200 hectares) account for about 20 percent of all farms; and more than 80 percent of all farm land is in farms above 100 hectares. The calibrated model implies that agricultural output is 1.4 percent of U.S. GDP, which is consistent with the data.

[8] Mean farm size in the model is simply the stock of land divided by the measure of farmers, i.e., $L/(5 * 0.0174) = 169 \rightarrow L = 14.7$.

Table 2.1: Parameter values and targets

Parameter	Value	Targets
Panel A		
A	1	Normalization
(ϕ_a, ϕ_m)	(1,1)	Assumption
β	$(0.96)^{10}$	Standard value
γ	0.11	Land share
Panel B		
λ_a	3.85	Dispersion, hourly earnings in agriculture
λ_m	2.34	Dispersion, hourly earnings in non-agriculture
θ_a	0.35	Age-earnings profile, agriculture
θ_m	0.25	Age-earnings profile, non-agriculture
(δ_a^1, δ_a^2)	(0.26, 0.8)	Age-earnings profile, agriculture
(δ_m^1, δ_m^2)	(0.40, 0.65)	Age-earnings profile, non-agriculture
L	14.7	Mean farm size
η	0.0046	Share of employment in agriculture
$\bar{a}$	0.07	Minimum consumption expenditure

2.4 Results

The question this paper is designed to answer is why cross-country productivity differences in agriculture are larger than those in the aggregate and in non-agriculture. I use the calibrated model to answer this question for a sample of 79 countries. Data on GDP per worker, real output per worker in agriculture and non-agriculture are from Caselli (2005). Data on arable land per worker is from Restuccia, Yang, and Zhu (2008).

Countries are assumed to be identical except for their land endowment and their levels of total factor productivity. In particular, they face the same distribution of initial skills, and the same technology for skill accumulation. Land endowment for each country is chosen such that their land endowment relative to the U.S. is the same as that in the data. I vary country-specific TFP such that real GDP per worker (measured at international prices, relative to the U.S.) in the model is the same as that in the data. Then I assess the model's implications for output per worker in each sector against those in the data.

2.4.1 Sectoral Productivity Differences

I present my results as follows. First I calculate the productivity gaps in agriculture, in the aggregate, and in non-agriculture, respectively, between the 90th percentile country and the 10th percentile country. Then I calculate how large is the gap in agriculture relative to that in the aggregate and that in non-agriculture. I repeat the same calculations when I compare the 90th percentile country with the 25th percentile country and the 50th percentile country.

Table 2.2 demonstrates that between the 90th percentile country and the 10th percentile country, the productivity gap in agriculture is 1.8 times larger than that in the aggregate, and 5.7 times larger than that in non-agriculture. In the data, this ratio is 2 and 10, respectively. Furthermore, my model performs better relative to the benchmark model in Lagakos and Waugh (2010): in their model, the corresponding numbers are 1.6 and 4.3.

Table 2.2: Labor productivity gap between 90th and 10th percentile country

Ratio of Productivity Gap	Model	Data
Agriculture/Aggregate	1.77	2
Agriculture/Non-Agriculture	5.67	10

Next I examine the model implied sectoral productivity for other countries in the sample. Table 2.3 presents the comparison between the 90th percentile country and the 25th percentile country. The comparison between the 90th percentile country and the 50th percentile country is summarized in Table 2.4. The model performs less well when we compare high and intermediate income countries (25th percentile and

Table 2.3: Labor productivity gap between 90th and 25th percentile country

Ratio of Productivity Gap	Model	Data
Agriculture/Aggregate	2.3	3.6
Agriculture/Non-Agriculture	2.9	11.5

50th percentile). The reason is that the minimum consumption constraint becomes increasingly less binding as income increases. On the one hand, intermediate income countries only have a slightly higher share of farmers in the labor force, compared to high income countries. Since individuals in all countries draw from the same distribution of initial skills, similar divisions of labor imply small differences in the endowed skills of farmers and workers. On the other hand, as economies move above the minimum consumption level, equilibrium interest rate varies only marginally with income, and so does skill accumulation. Hence, the model fails to generate large differences in labor productivity.

2.4.2 The Importance of Skill Accumulation

How important is skill accumulation in generating the productivity differences? I address this question here. From Lemma 1, all individuals in a sector choose the same sequence of time investment, and enjoy the same growth in efficiency over time. Exploiting this fact, I rewrite aggregate production in agriculture and non-agriculture

Table 2.4: Labor productivity gap between 90th and 50th percentile country

Ratio of Productivity Gap	Model	Data
Agriculture/Aggregate	1.67	3.6
Agriculture/Non-Agriculture	1.67	5.8

as

$$Y_a = A \cdot \left[\sum_{\tau=1}^{T} \frac{z_{a,\tau}}{z_{a,1}}(1-s_{a,\tau})\right]^{1-\gamma} \cdot \left[\int_{j\in\Omega_{a,1}} z^j_{a,1} dG^j\right]^{1-\gamma} \cdot L^\gamma, \tag{2.8}$$

$$Y_m = A \cdot \left[\sum_{\tau=1}^{T} \frac{z_{m,\tau}}{z_{m,1}}(1-s_{m,\tau})\right] \cdot \left[\int_{j\in\Omega_{m,1}} z^j_{m,1} dG^j\right]. \tag{2.9}$$

Recall that at any point in time the measure of population is T. In a stationary equilibrium, the measure of farmers is given by $N_a = T \cdot \int_{j\in\Omega_{a,1}} dG^j$. Similarly, the measure of workers in non-agriculture is $N_m = T \cdot \int_{j\in\Omega_{m,1}} dG^j$. Now real output per worker in each sector can be expressed as

$$\frac{Y_a}{N_a} = \underbrace{A}_{TFP} \cdot \underbrace{\left[\sum_{\tau=1}^{T} \frac{z_{a,\tau}}{z_{a,1}}(1-s_{a,\tau})/T\right]^{1-\gamma}}_{Accumulation} \cdot \underbrace{E[z^j_{a,1}|j\in\Omega_{a,1}]^{1-\gamma}}_{Specialization} \cdot \underbrace{\left(\frac{L}{N_a}\right)^\gamma}_{Land-per-farmer} \tag{2.10}$$

$$\frac{Y_m}{N_m} = \underbrace{A}_{TFP} \cdot \underbrace{\left[\sum_{\tau=1}^{T} \frac{z_{m,\tau}}{z_{m,1}}(1-s_{m,\tau})/T\right]}_{Accumulation} \cdot \underbrace{E[z^j_{m,1}|j\in\Omega_{m,1}]}_{Specialization} \tag{2.11}$$

The model mechanisms are revealed in equations (2.10) and (2.11). Low TFP reduces output per worker in both sectors directly, and affects the quality of labor indirectly. The term $E[z^j_{a,1}|j\in\Omega_{a,1}]$ is the average initial agricultural skill of farmers. Similarly,

$E[z_{m,1}^j | j \in \Omega_{m,1}]$ is the average initial non-agricultural skill of workers. The "specialization" effect dictates that $E[z_{a,1}^j | j \in \Omega_{a,1}]$ increases with TFP, but $E[z_{m,1}^j | j \in \Omega_{m,1}]$ decreases with TFP. The reason is the following. Because of the minimum consumption constraint, an exogenous reduction in TFP raises the relative price of output in agriculture. More individuals with low initial skill in agriculture move out of non-agriculture into agriculture, leaving in non-agriculture those who are truly talented in it. As a result, the average farmer has lower initial skill in agriculture, but the average worker has higher initial skill in non-agriculture. This "specialization" effect, as highlighted in Lagakos and Waugh (2010), is the main reason the model generates labor productivity differences that are larger in agriculture and smaller in non-agriculture, compared to differences in aggregate income per worker.

The other two indirect effects of TFP, "accumulation" and "land-per-farmer" are unique to this paper. The "accumulation" effect, as captured by the term $\sum_{\tau=1}^{T} \frac{z_{i,\tau}}{z_{i,1}}(1 - s_{i,\tau})$, summarizes the growth of skill over the life cycle. As illustrated in section 2.4 using a simpler two-period model, such productivity growth increases with TFP (see equation (2.7)). In agriculture, the farmers in low TFP economies have on average low initial skill. The accumulation effect further implies that they also invest little over the life cycle to improve their skills. This leads to larger differences in output per worker in agriculture. Low TFP also reduces the optimal scale of production in agriculture. In equation (2.10), $\frac{L}{N_a}$ is the average quantity of land per farmer, which can also be interpreted as the average farm size because one farm is associated with a single farmer in the model. The minimum consumption constraint necessitates a larger measure of farmers when TFP is low, leading to reduced farm size and lowered labor productivity in agriculture.

To quantify the contribution of each of these forces, I perform the following decomposition exercise. Starting from a model with homogenous labor, I ask if such a model can explain the sectoral productivity differences, given exogenous differences in land endowment.[9] The fist row of Table 2.5 demonstrates that such a model would not be able to explain observed sectoral productivity differences. When exogenous differences in TFP is incorporated, the model generates productivity differences in agriculture that are larger than those in the aggregate and in non-agriculture. However, quantitatively, these productivity differences are inconsistent with the data.

Next, I introduce individual heterogeneity in their initial skills (of both agriculture and non-agriculture production). However, they do not accumulate skills over the life cycle.[10] As discussed before, the differences in TFP affect the allocation of skills across sector. Hence, the model generates productivity differences in agriculture that are twice as large as those in the aggregate, and 4 times larger than those in non-agriculture. When individuals are further allowed to accumulate skills, the ratio of agricultural productivity gap to aggregate productivity gap drops to 1.8, but the ratio of agricultural productivity gap to non-agricultural productivity gap increases to 5.7.

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[9]This corresponds to the case $z_a = z_m = z$. The technology in agriculture is $Y_a = A\bar{Z}^{1-\gamma}L^{\gamma}$, and in non-agriculture is $Y_m = A\bar{Z}$, where $\bar{Z} = \int zdG(z)$.

[10]This is done by setting $\theta_a = \theta_m = 0$.

Table 2.5: Decomposing productivity gap between 90th and 10th percentile country

	$\frac{\text{Agriculture}}{\text{Aggregate}}$	$\frac{\text{Agriculture}}{\text{Non-agriculture}}$
+ Land endowment	1.01	1.01
+ TFP	1.15	1.33
+ Specialization	2.16	4.25
+ Accumulation	1.77	5.67

2.4.3 The Size Distribution of Farms

A salient feature of farming in poor countries is the dominance of small farms (less than 5 hectares). For the poorest 10 percent of the countries in my sample, I calculate the farm size distributions using data from 1990 World Census of Agriculture, administered by the Food and Agriculture Organization (FAO).[11] In these countries, 90 percent of the farms are smaller than 5 hectares. Moreover, 61 percent of farm land is in these small farms. These statistics contrast sharply for example with those for the U.S., where less than 10 percent of all farms are below 5 hectares, and the land in these farms is a negligible share of total farm land.

[11] The poorest 10 percent countries are Ethiopia, Burkina Faso, Nepal, Mozambique, Uganda, Malawi, Mali and India.

I compare the farm size distributions generated from the model with those in the data for the poorest 10 percent of the countries in my sample. Table 2.6 demonstrates that the model is able to capture the key features of the farm size distribution in those poor countries, relying only on differences in aggregate TFP. In terms of the size distribution of farms, the model predicts that 89 percent of all farms are less than 5 hectares (91 percent in the data), and only 2.5 percent of farms exceed 10 hectares in size (2.7 percent in the data). In terms of the distribution of farm land, the model predicts that 84 percent of all farm land is in farms less than 5 hectares (62 percent in the data), and only 5.1 percent of farm land is in farms over 10 hectares (12.6 percent in the data).

In contrast to small scale farming in poor countries, farms in rich countries are gigantic.[12] Table 2.7 shows that the model replicates the large scale production in agriculture of rich countries fairly well. For example, both in the model and in the data, large farms ($>$ 100 hectares) account for roughly one third of all farms; these large farms also account for one third of all farm land.

What explains the stark differences in farm size distribution between rich and poor countries? In a recent paper, Adamopoulos and Restuccia (2011) argue that these differences in the size distribution of farms are a result of farm level distortions in poor countries. Here I offer an alternative interpretation. Instead of size-dependent distortions, the prevalence of small farms in poor countries is a joint result of insuf-

[12]The richest 10 percent countries are Norway, Australia, Italy, Canada, Netherlands, Switzerland and United States.

Table 2.6: Size distribution of farms in the poorest 10 percent of countries: model and data

	Data	Model
Share of Farmers in the Labor Force	0.85	0.74
Mean Farm Size (Hectares)	1.46	2.49
Size Distribution (%)		
Farms $<$ 5 Hectares	90.7	89.1
Farms $>$ 10 Hectares	2.7	2.48
Land Distribution (%)		
Farms $<$ 5 Hectares	61.5	84.2
Farms $>$ 10 Hectares	12.6	5.1

Table 2.7: Size distribution of farms in the richest 10 percent of countries: model and data

	Data	Model
Share of Farmers in the Labor Force	3.8%	2.5%
Mean Farm Size (Hectares)	524	140
Size Distribution (%)		
Farms < 20 Hectares	48.6	31.2
Farms > 100 Hectares	32.9	33.6
Land Distribution (%)		
Farms < 20 Hectares	33.4	26.1
Farms > 100 Hectares	30.0	37.6

ficient specialization and limited skill accumulation. In a nutshell, farms are small because farmers have low skill to begin with; farms stay small because farmers do not invest to improve productivity.[13]

2.4.4 Other Implications

In this section, I examine other implications of the model. These implications include sectoral labor allocation, the relative price of agriculture output, and the life-cycle productivity growth of farmers.

The model speaks to the division of labor between farmers and non-agriculture workers. I compute the share of farmers in the labor force in the data as follows. The share of employment in agriculture is directly available from the 2004 Statistical Year Book published by the Food and Agriculture Organization. However, agriculture employment consists of both self-employed farmers and wage workers in agriculture. To separate the two, I use national labor surveys compiled by the International Labor Organization (ILO).[14] Figure 2.1 plots on the horizontal axis PPP GDP per worker relative to that of the U.S., and on the vertical axis the share of farmers in the labor force in the model and in the data. The scatter plot is the data and the smooth curve

[13]Bhattacharya (2009) shows that a standard Lucas's span-of-control model with managerial skill investment accounts for bulk of the cross-country differences in establishment size distribution. Bhattacharya, Guner, and Ventura (2011) argue that when there is endogenous managerial skill accumulation, size-dependent distortions have amplified effects on aggregate output and plant size distribution.

[14]The labor survey classifies employment in agriculture into four categories: employer and own account, unpaid family member, employee, and unclassified. I treat the first two categories as equivalent to farmers in the model. In poor countries, farmers make up more than 90 percent of the agriculture labor force. See appendix B.2.

refers to the model. The share of farmers in the model declines from 90 percent in the poorest country to less than 3 percent in the richest country as observed in the data.

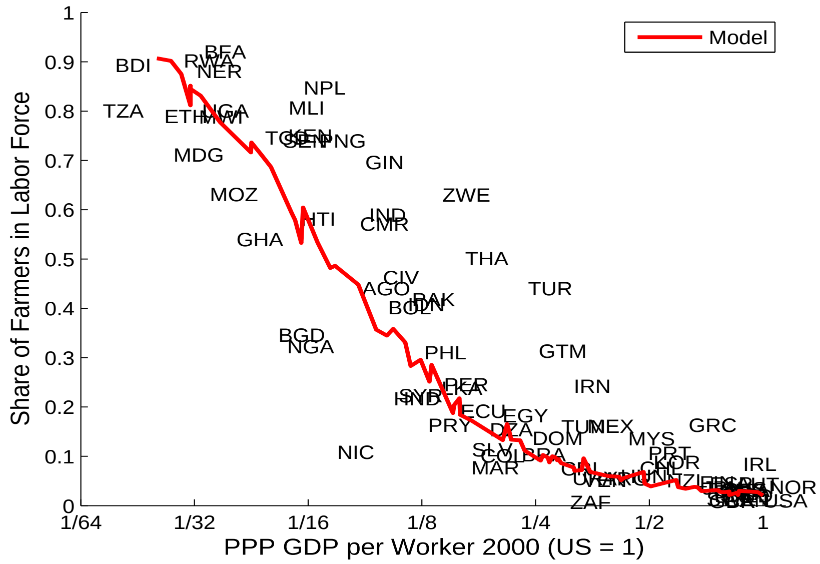


Figure 2.1: The share of farmers in the labor force: model and data

In the model, TFP alters the allocation of skills across sectors by changing the relative price of output in agriculture. Therefore, the model implies that the price of output in agriculture relative to that in non-agriculture decreases with the level of income. To verify this implication, I compute the price of food consumption relative to that of non-food consumption using data from the 2005 International Comparison Program of the World Bank. The relative price in the data is about 2.3 times higher in the 10th percentile country, relative to that in the 90th percentile country. The model overstates this price difference; the relative price is about 5 times higher in the 10th percentile country.

One of the implication from the model is that skill accumulation is discouraged when income is low. Consider the comparison between Nepal and U.S. There is a factor of 22 difference in aggregate income per worker. The model predicts that the productivity growth (measured by growth in farm size) of a farmer between age 25 and 45 is about 13 percent lower in Nepal, relative to that in the U.S. In the data, I find that the size growth is 19 percent lower in Nepal, relative to that in the U.S.

2.5 A Model with Skill Externality

It is hard to argue that the state of technology in agriculture is the same in developing and developed countries. The mechanized, large-scale agricultural production in developed countries contrasts sharply with the labor-intensive, small-scale family production that typifies agriculture in developing countries. In this paper, these technological differences have been summarized using an exogenous TFP term. However, much of the technological differences are due to slow adoption of new technology (Evenson and Gollin (2003), Restuccia, Yang, and Zhu (2008)). In a very stylized way, adopting a new technology is very similar to accumulating skill. Both require existing knowledge (current skill) and learning (time investment). This interpretation is particularly suitable if a new technology represents continuous improvements of current practices. The question is what has prevented the adoption of productive technology in developing countries? Or using the very stylized interpretation, what has prevented the farmers from accumulating (technology embodied) skill?

The answer given in this paper so far is that aggregate barriers like low TFP have discouraged the accumulation of skills. Here I consider the importance of learning from others. Farmers' decisions to adopt new technologies is shown to critically depend on existing knowledge of the technology their neighbors possess (Foster and Rosenzweig (1995), Conley and Udry (2010)). In this section, I propose a simple way to incorporate this learning externality into my model. Under parameterizations that are exploratory in nature, I assess the importance of such externality in understanding cross-country productivity differences.

To incorporate the effect of learning from others, I modify the skill accumulation technology. In particular, the return to investment in skill accumulation depends also on the average skill within the sector. Specifically, the law of motion for skill from age τ to $\tau + 1$ is

$$z_{i,\tau+1} = (1 - \delta_i) z_{i,\tau} + \bar{Z}_i^{\zeta} z_{i,\tau} s_{\tau}^{\theta_i}, \tag{2.12}$$

where $\bar{Z}_i$ is the average sector-specific skill in sector i. The parameter ζ controls the extent of skill externality. The technology in the benchmark model corresponds to the case of $\zeta = 0$. Empirically estimating the magnitude of human capital externality is an object of ongoing research. Existing estimates of human capital externality fall in the range of 0 to 10 percent. I experiment with two different values: $\zeta = 0.05$ and $\zeta = 0.1$.

Individuals solve the optimization problems as outlined in section 2.2. They have full information about the effects average skill has on the marginal return to their own investments; however, they do not internalize the positive externality their investments have on the average skill within a sector. Individuals have rational expectations about the evolution of sectoral average skill over time. In a stationary equilibrium, the following two conditions have to be satisfied.

$$\bar{Z}_a = \left[\sum_{\tau=1}^{T} \frac{z_{a,\tau}}{z_{a,1}}/T\right] \cdot \int_{j\in\Omega_{a,1}} z_{a,1}^j dG^j, \tag{2.13}$$

$$\bar{Z}_m = \left[\sum_{\tau=1}^{T} \frac{z_{a,\tau}}{z_{a,1}}/T\right] \cdot \int_{j\in\Omega_{m,1}} z_{m,1}^j dG^j. \tag{2.14}$$

As before, $\int_{j\in\Omega_{i,1}} z_{i,1}^j dG^j$ is the average initial skills of age-1 individuals in sector i. These expressions follow from Lemma 1 and the fact that population is constant. Equations (2.13) and (2.14) define a system of non-linear equations in two unknowns $(\bar{Z}_a, \bar{Z}_m)$.

Given the magnitude of externality, I recalibrate the model to the U.S., matching the targets explained in section 3. In an effort to isolate the extra effects coming from externality, I assume the same distribution of initial skills as in the model without externality. The cost is that in some cases, the model is no long able to match the relative mean earnings between agriculture and non-agriculture. Then I again vary country-specific TFP to match real GDP per worker in the data, and compare model's predictions of output per worker in agriculture and non-agriculture against those in the data.

Table 2.8 demonstrates that a model with externality performs better accounting for cross-country productivity differences in agriculture and non-agriculture. In

Table 2.8: Productivity gap between 90th and 10th percentile with different magnitudes of externality

Ratio of Productivity Gap	$\zeta = 0$	$\zeta = 0.05$	$\zeta = 0.1$	Data
Agriculture/Aggregate	1.8	1.86	1.9	2
Agriculture/Non-agriculture	5.6	7	9.7	10
Relative Mean Earnings				
Agriculture/Non-agriculture	0.69	0.69	0.7	0.69

fact, when the externality is strong enough ($\zeta = 0.1$), the model accounts for almost all of the differences in output per worker in both agriculture and non-agriculture. Since I use the same distribution of initial skills as in the model without externality, the improved performance most likely reflects the increased importance of skill accumulation.

2.6 Conclusion

I developed a life cycle model of occupational choice and on-the-job skill accumulation to quantitatively explain sectoral productivity differences across countries. The calibrated model reproduces both cross-sectional and life-cycle features of earnings in U.S. data. Even though countries differ only in sector-neutral TFP, the model generates productivity differences in agriculture and non-agriculture that are quantitatively consistent with data. Moreover, the model captures other stylized observations in poor countries including the high share of farmers in the labor force and the prevalence of small farms.

I have chosen TFP to reproduce observed disparity in real GDP per worker. The implied cross-country disparity in TFP is much larger than those from standard development accounting exercises (Hall and Jones (1999), Caselli (2005)). This is because I do not have physical capital in my model. The differences in TFP in my model reflect, at least partially, the differences in physical capital across countries. A natural extension is to introduce physical capital into the current framework. In particular, if capital and skills are complements, the model might be able to account for more of the productivity differences across countries.

APPENDIX A
CHAPTER 1

A.1 Data Description

- **World Census of Agriculture** This 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. 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. `http://www.fao.org/economic/ess/ess-data/ess-wca`

- **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`.

- **Working Days by Age of Farm Operator** The data is calculated from 2007 U.S. census of agriculture. Panel A reports the number of days *off* the farm. I assume 250 working days a year, and use the midpoint of the interval as the interval average. Panel B reports the fraction of time off the farm by age group.

Table A.1: Working days by age of farm operator

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	

A.2 Proof

Proof of Lemma 1:

Recall that profit function is linear in skill, i.e.,

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

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

$$\max_{s_t} : \sum_{t=1}^{T} R^{1-t}\cdot z_t\cdot(1-s_t)$$

$$s.t : z_{t+1} = z_t(1+s_t^{\theta}).$$

The optimal path of investment can be solved using backward induction. Clearly, $s_T = 0$. The problem at period T-1 can be written as

$$\max_{s_{T-1}}: \ z_{T-1}(1 - s_{T-1}) + z_{T-1}(1 + s_{T-1}^{\theta}) \cdot R^{-1}$$

the optimal time is given by $s_{T-1} = (\theta/R)^{1/(1-\theta)}$. Now define $d_{T-1} = (1 - s_{T-1}) + (1 + s_{T-1}^{\theta})/R$, the problem at period T-2 can be written as

$$\max_{s_{T-2}}: \ z_{T-2}(1 - s_{T-2}) + z_{T-2}(1 + s_{T-2}^{\theta}) \cdot d_{T-1} \cdot R^{-1}$$

The solution has a recursive structure

$$S_T = 0, \quad d_T = 1$$

$$s_{t-1} = (\theta d_t/R)^{\frac{1}{1-\theta}}, \quad d_{t-1} = (1 - s_{t-1}) + (1 + s_{t-1}^{\theta})/R, \quad t = 2, ..., T.$$

A.3 Numerical Analysis

Table A.2: Age-hour profile: model and data

Age	25-34	35-44	45-54	55-64	65+
Data	0.09	0.17	0.17	0.23	0.34
Model	0.08	0.17	0.20	0.26	0.29

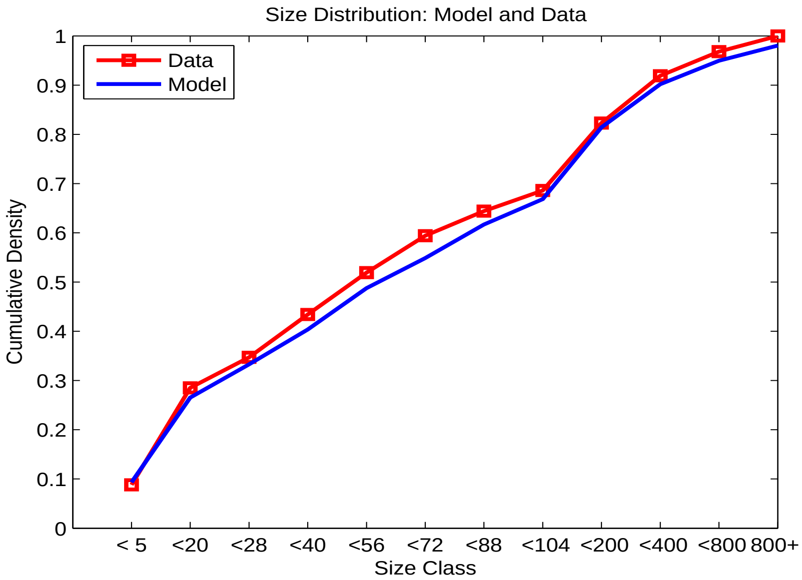


Figure A.1: Size distribution of farms: model and data

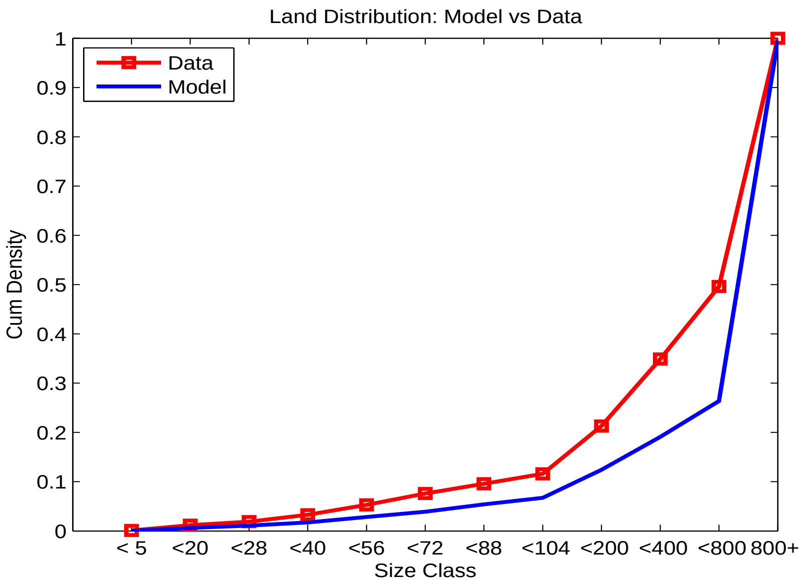


Figure A.2: Land distribution of farms: model and data

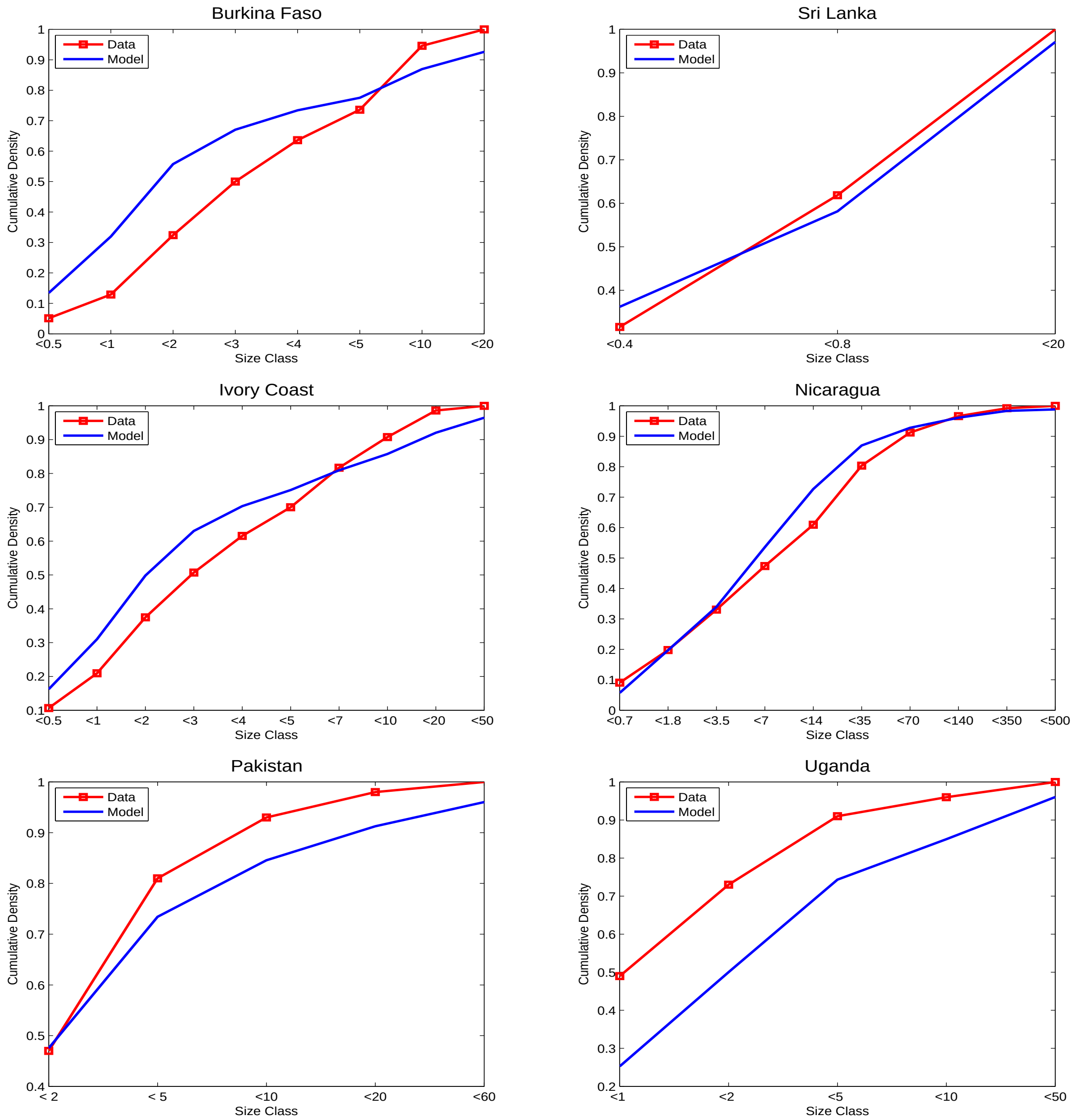


Figure A.3: Size distribution of farms in low income countries: model and data

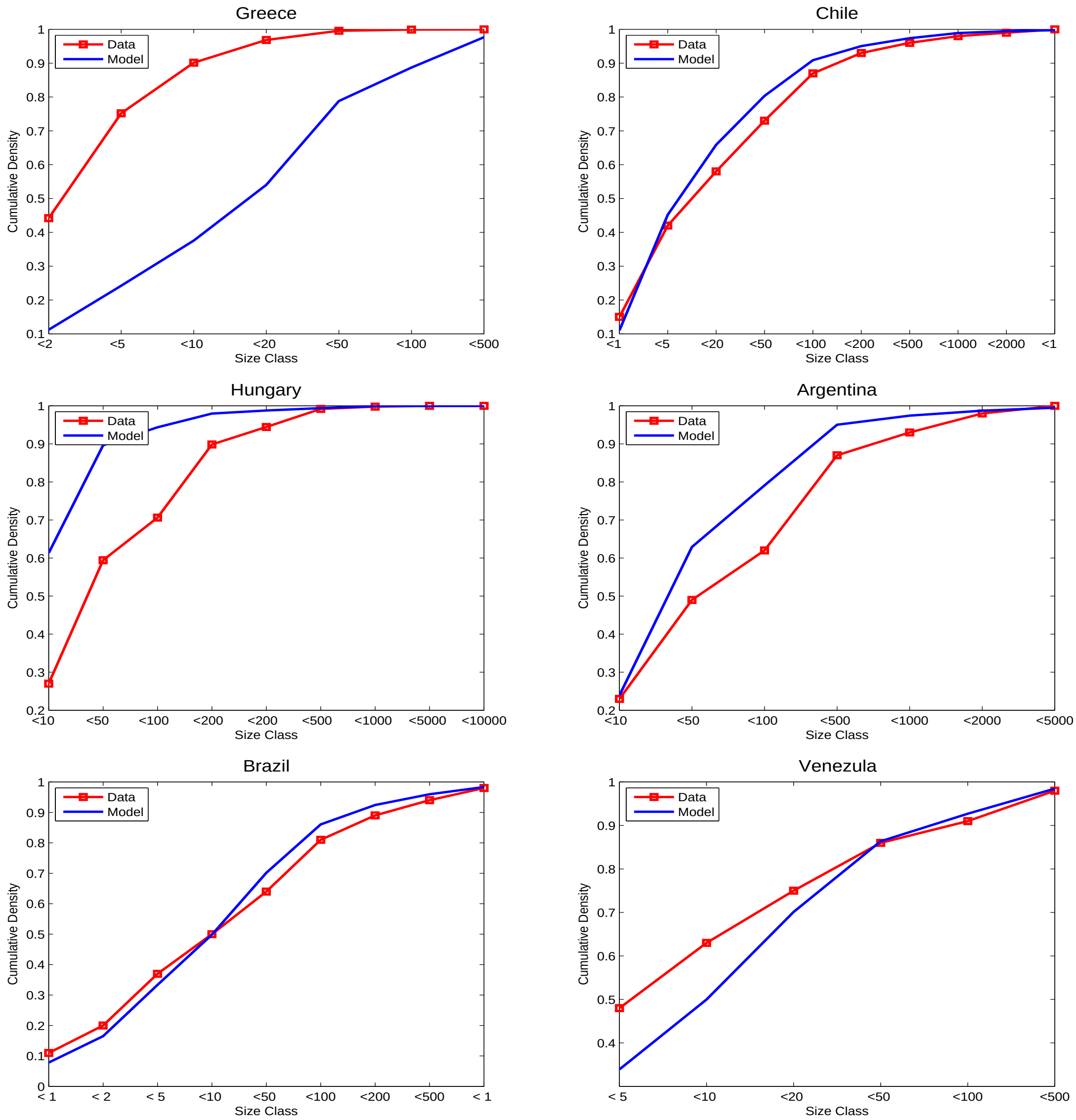


Figure A.4: Size distribution of farms in median income countries: model and data

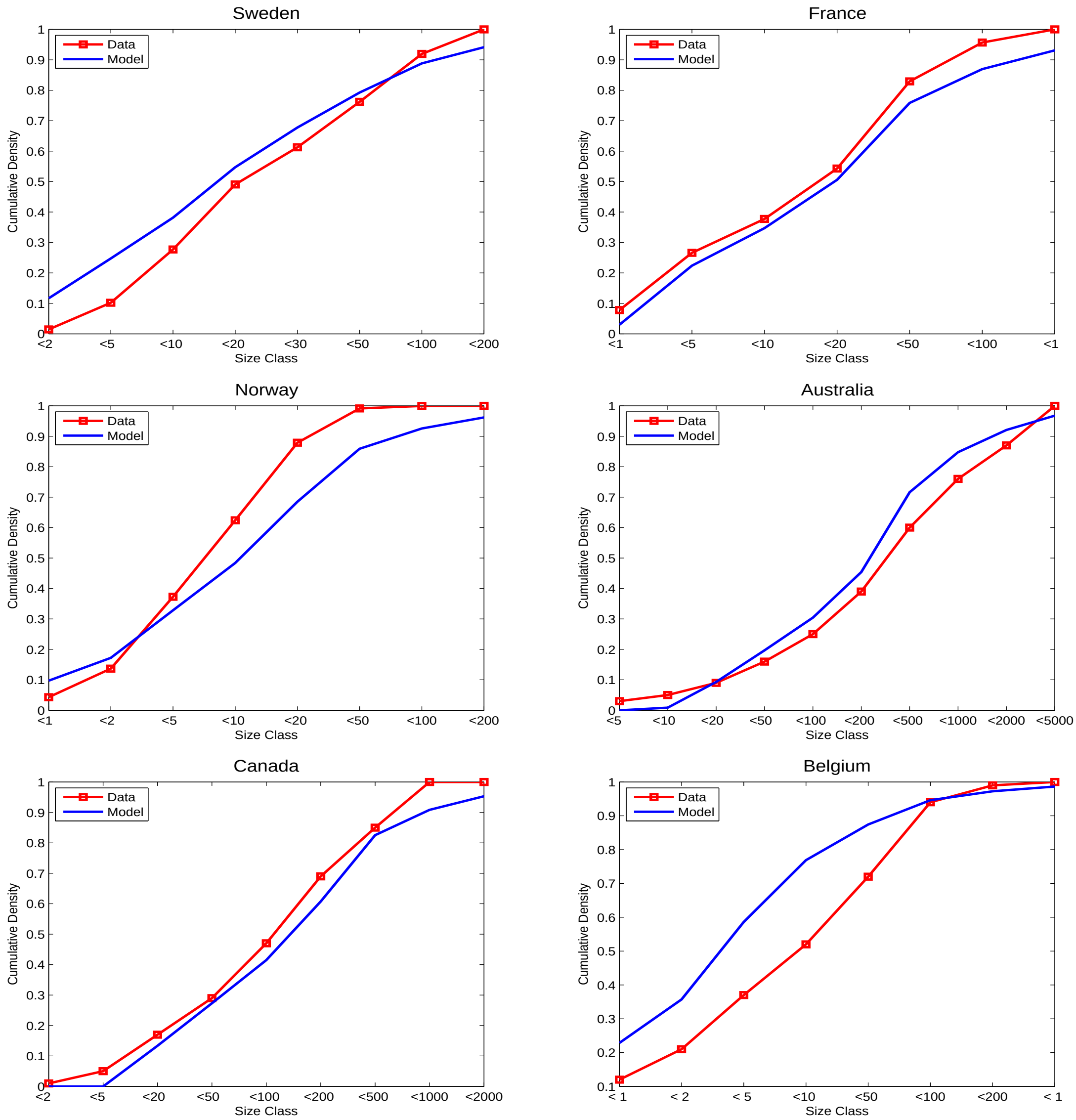


Figure A.5: Size distribution of farms in high income countries: model and data

APPENDIX B
CHAPTER 2

B.1 Data Description

- **Cross-Country Productivity Differences** Real output per worker in agriculture and non-agriculture is available from Caselli (2005). Table B.1 presents productivity differences between the 90th percentile country and the 10th percentile country in the world income distribution.

Table B.1: Cross-country productivity differences: the role of capital

Labor Productivity Gap	Unadjusted for Capital	Adjusted for Capital
Agriculture	45	11.5
Aggregate	22	4.5
Non-agriculture	4	2.3

The message to take away from the table is that labor productivity differences in agriculture are much larger than those in the aggregate and in non-agriculture. A legitimate concern is that labor productivity differences are due to differences in physical capital. Addressing this concern requires data on sectorial capital, which is not available for a larger set of countries. I instead follow the approach in Caselli (2005) and infer the capital stock in each sector indirectly. More specifically, I assume the following sectorial technology

$$Y_a = TFP_a \cdot K_a^{\gamma} N_a^{\beta} L^{1-\gamma-\beta},$$

$$Y_m = TFP_m \cdot K_m^{\alpha} N_m^{1-\alpha}.$$

I also assume perfect mobility of capital across sectors, which implies the following optimality condition

$$\gamma \frac{P_a Y_a}{K_a} = \alpha \frac{P_m Y_m}{K_m},$$

and the resources constraint that $K_a + K_m = K$. Aggregate capital stock K, and sectorial output at domestic prices, $P_a Y_a$ and $P_m Y_m$, are directly available from Penn World Tables and World Development Indicator. I hence can infer the sectorial capital stock by solving the system of equations. I also obtain L as stock of arable land per worker from data. Given (K_a, K_m, L), and sectorial labor allocation (N_a, N_m), I back out the sectorial TFP measures (TFP_a, TFP_m). The table below summaries the dispersion of TFP across countries at the aggregate as well as the sectorial levels.

Even after accounting for physical capital differences, productivity dispersion remains much larger in agriculture compared to those in the aggregate and in non-agriculture.

- **U.S. Cross-sectional Earnings** The cross-sectional data is extracted from 2007 Current Population Survey, available in IPUMS-CPS (King, Ruggles, Alexander, Flood, Genadek, Schroeder, Trampe, and Vick (2010)). I restrict our sample to include only individuals 25-65 with non-missing income and hours, who work at least 35 hours per week and at least 1750 hours per year. Earnings are computed as the sum of wage and salaries income, business income, and farm income. Individuals earning less than Federal minimum wage are also excluded. My sample consists of 52,152 observations, of which 534 are working in the agriculture sector, and 51,618 are working in the non-agriculture sector. In assigning sectors, I label individuals with occupation code 20, 21, 600, 604, 605, 600, 612 as working in agriculture, and the individuals with other occupation codes as working non-agriculture. Within agriculture, I further group individuals with code 20, 21, and 600 as farmers, and the rest as workers.[1]

– **Mean and Dispersions of Earnings**

Average hourly earnings are 17 in agriculture, and 25 in non-agriculture, both expressed in 2007 U.S. dollars. Earnings are less dispersed in agriculture, relative to non-agriculture. The standard deviation of log normalized hourly earnings is 0.48 in agriculture, and 0.58 in non-agriculture. Within agriculture, the mean hourly earnings of wage/salaries workers are 13, and for farmers are 20. The standard deviation of normalized log hourly earnings of wage/salaries workers is 0.39, which is substantially lower than that of farmers (0.56).

[1] Occupations code 20, 21, 600 corresponds to farm/ranch managers, farmers and ranchers, and first line supervisor/managers of fishing and forestry workers.

– **Age-Earnings Profile**

I compute the mean hourly earnings of different age groups in agriculture and non-agriculture. In agriculture, I also construct age-earnings profiles separately for farmers and wage/salaries workers. The main message is that the age-earnings profile displays a well-known hump-shape in non-agriculture as well as for farmers in agriculture. For wage/salaries workers in agriculture, the age-earnings profile is essentially flat.

Table B.2: Mean hourly earnings by age group, in agriculture and non-agriculture

Age	Non-agriculture	Agriculture	
		Farmer	Wage Worker
$<= 25$	16	13	12
$26 - 34$	21	17	14
$35 - 44$	26	20	13
$45 - 54$	27	21	12
$55 - 60$	26	20	10

Note: numbers reported are in 2007 U.S. dollars.

- **Labor Force Composition in Agriculture** Self-employment is a predominant form of employment in agriculture, both in developed and developing countries. For the US, farmers make up 59 percent of total employment in agriculture, and wage/salary workers make up 41 percent. These shares are consistent with that reported by The Bureau of Labor Statistic (BLS (2010)BLS).

  Across countries, I use national labor surveys complied by the International Labor Organization (ILO). I compute the fraction of individuals characterized as one of the following types: employers and own account workers, employees, unpaid family members, and unclassified. Figure B.1 plots the share of employers, own account worker and unpaid family members on the vertical axis, and PPP per capita income on the horizontal axis. Two observations are immediate: 1) most of the labor force in agriculture are employers, own account workers, and unpaid family members; 2) the composition of employment in agriculture does not vary systematically with income levels.

- **Productivity Growth of Farmers: U.S. Cross Section** While the age-earnings profile constructed from CPS data suggests productivity growth over farmer's life cycle, I note the following concerns. First, the earnings data in CPS contains non-farm wage and business income. Hence the variation in earnings might reflect changes in off-farm employment and asset income, rather than the changes in the farmer's productivity in agricultural production. Second, it is well known that government payments and transfers are an important source of farm income. In CPS, it is not possible to adjust for government payments.

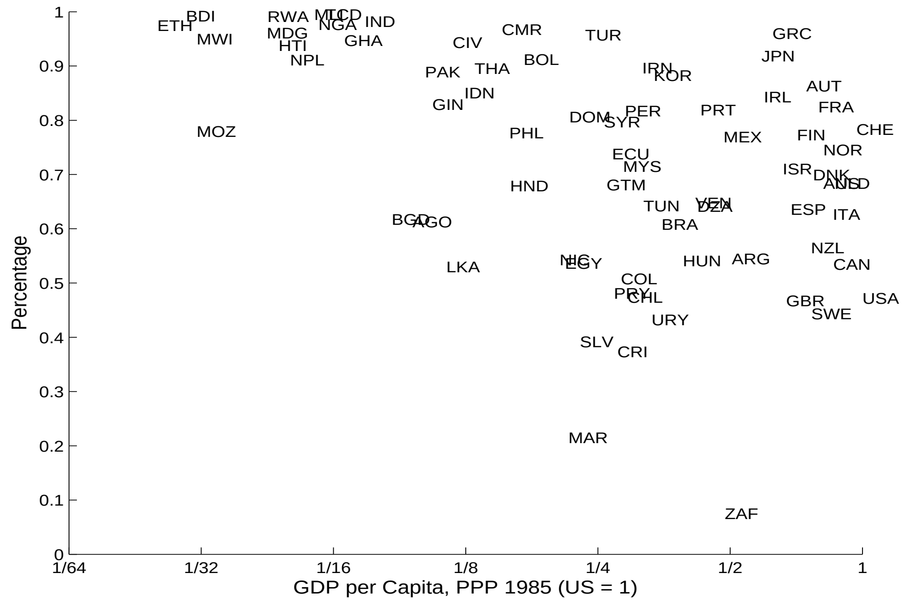


Figure B.1: Share of self-employed farmers in agriculture labor force

Keeping these concerns in mind, I turn to balance sheet data from Census of Agriculture. These data pertain to farm operators whose primary occupation is farming, and have rich information about production expenses and government payments. I present three measures of farm operator's productivity. The first one is the land size of a farm. The second one is operational income net of government transfers. The last one is a Solow-type residual, which is computed using information on gross output and factors of production (intermediate goods, physical capital, land and hired labor). All three measures point to significant productivity gain over the life-cycle of farm operators.

- **Productivity Growth of Farmers: International Comparison** International data on productivity growth is limited. Here I provide a case study of

Table B.3: Productivity growth of farmers in 2007 U.S. cross-section

Age	< 25	$25 - 34$	35-44	45-54	55-64
Farm Size	1.00	1.43	2.00	2.19	1.87
Operation Income	1.00	2.03	3.21	3.10	1.99
Solow Residual	1.00	1.24	1.35	1.28	0.87

Note: productivity of farm operator less than 25 is normalized to be 1 in all three cases.

three countries: United States, Nepal and Sri Lanka.[2] I find that productivity gain by farmers, as measured by the increase in farm size over the life cycle, is much less pronounced in poor countries like Nepal and Sri Lanka, relative to that in the U.S. Figure B.2 plots the age-size profiles in these three countries. The slope of the profile is much steeper in the U.S., relative to that in the two less developed countries.

- **Productivity Growth of Farmers: U.S. Historical** Facing limited international data, I turn to U.S. historical census data from 1964 to 2007. From each census, I construct the age-size profile from the current cross-section of farm operators. I find that the slope of the profile increases with the level of income.

[2]Data for Nepal is from Nepal National Census of Agriculture, 2000/2001, available through `http://www.cbs.gov.np/nada/index.php/catalog/8`. For Sri Lanka, data is from 2002 Census of Agriculture, available through `http://www.statistics.gov.lk/agriculture/AGC2002`.

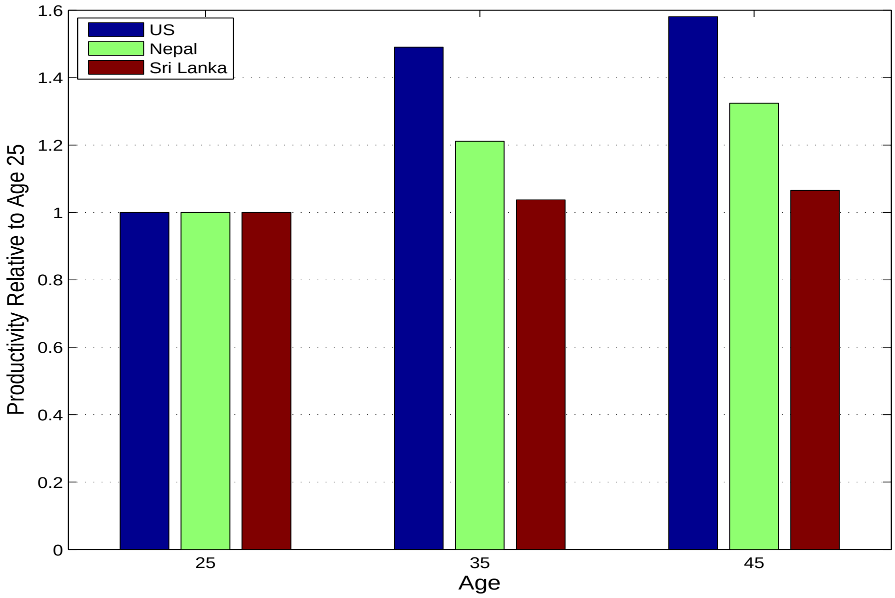
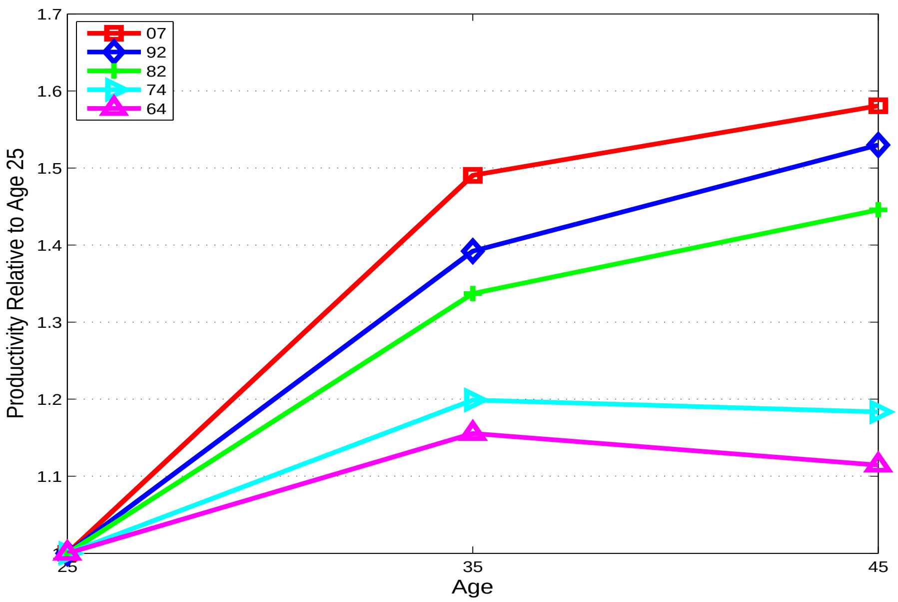


Figure B.2: Productivity growth of farmers in U.S., Nepal and Sri Lanka

This observation is demonstrated in panel (a) of Figure B.4.

I note that this way of constructing age-size profile, while informative, could be misleading as well. The reason is that in each census year, observations at different nodes of the age-size profile represent different cohorts. As a result, the variation in size over age can simply reflect cohort specific information such as education. To overcome this problem, I compute the change in farm size by creating synthetic cohorts. For example, I compute the increase in size between the age 25-34 group in 1969 census and the under 25 group in 1964 census. This increase is a reasonable proxy of the productivity growth experienced by the 1964 cohort between 1964 and 1969. I compute the productivity growth between age 20 and 25, and between age 25 and 35 using this method. The resulting time series is plotted on panel (b) of Figure B.4.



Note: number on the horizontal axis depicts the level of productivity relative to that at age 25.

Figure B.3: Productivity growth of farmer in historical U.S. cross section

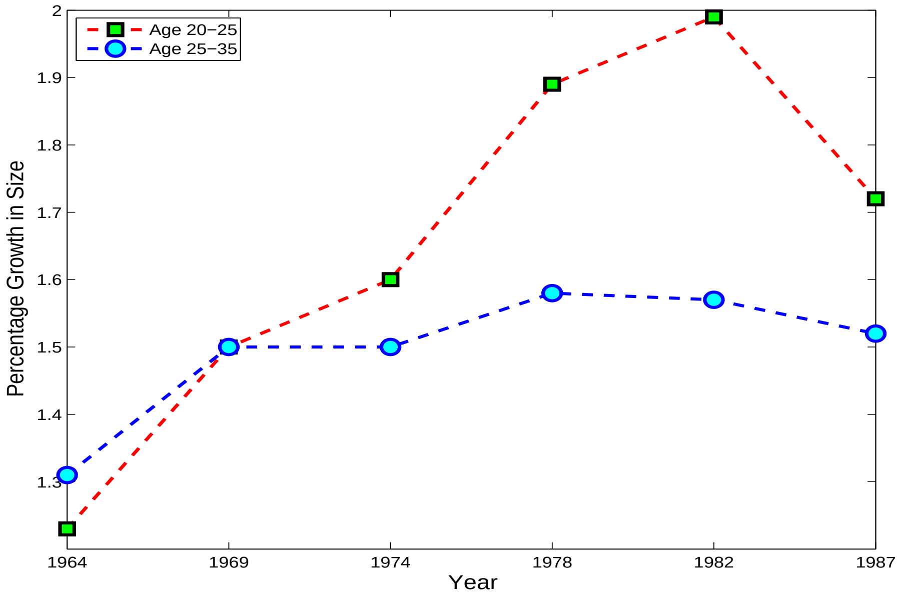
B.2 Proof

Proof of Lemma 1. *First note that earnings of farmers and workers are linear in the relevant skill. Their skill accumulation problem is*

$$\max_{s_\tau} \sum_{\tau=1}^{T} z_\tau(1-s_\tau)\cdot R^{1-\tau}$$

Skill investment is not optimal in the last period, so the problem in the second last period is

$$\max_{s}\ z(1-s)+R^{-1}\left[(1-\delta)z+zs^{\theta}\right],$$



Note: the green dotted line depicts the change in productivity growth between age 20 to 25. The blue dotted line depicts the change in productivity growth between age 25 to 35.

Figure B.4: Productivity growth of farmer in U.S. time series using synthetic cohorts

and optimal investment is $s = \left(\frac{\theta}{R}\right)^{1/(1-\theta)}$. *Discounted income can be written as* $z\Lambda$, *where*

$$\Lambda = \left[1 - \left(\frac{\theta}{R}\right)^{1/(1-\theta)}\right] + R^{-1}\left[(1-\delta) + \left(\frac{\theta}{R}\right)^{\theta/(1-\theta)}\right]$$

Now the problem one period before can be written in a similar way as

$$\max_s \; z(1-s) + \Lambda R^{-1}\left[(1-\delta)z + zs^{\theta}\right],$$

the optimal decision is given by $s = \left(\frac{\theta\Lambda}{R}\right)^{1/(1-\theta)}$, *and does not depend on beginning of period skill. We can write discounted income as* $\Lambda' z$, *where* Λ' *is a function of only* θ, δ *and* R. *Repeating these steps yields a sequence of time investment that is independent of initial skill.*

B.3 Calibration and Model Implications

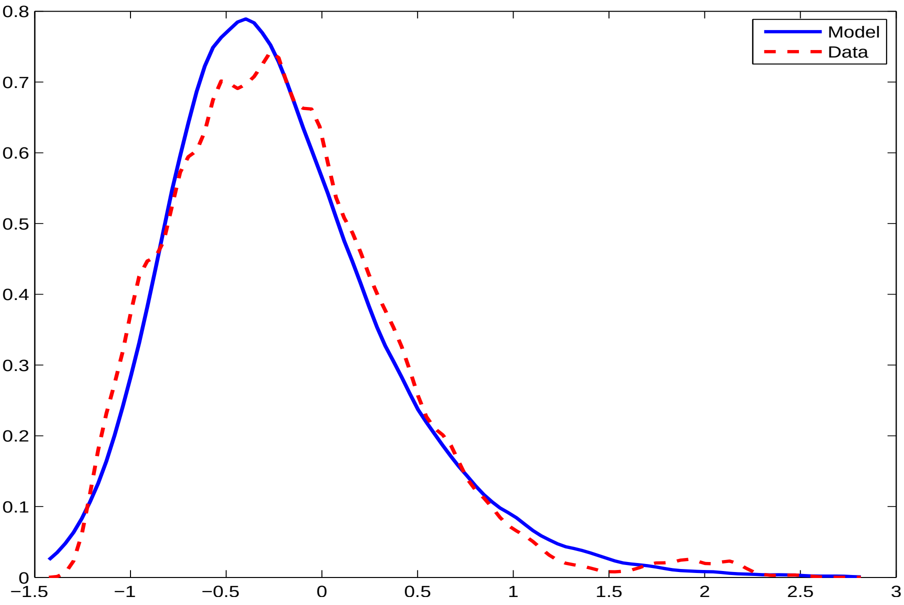


Figure B.5: Distribution of hourly earnings in the aggregate: model and data

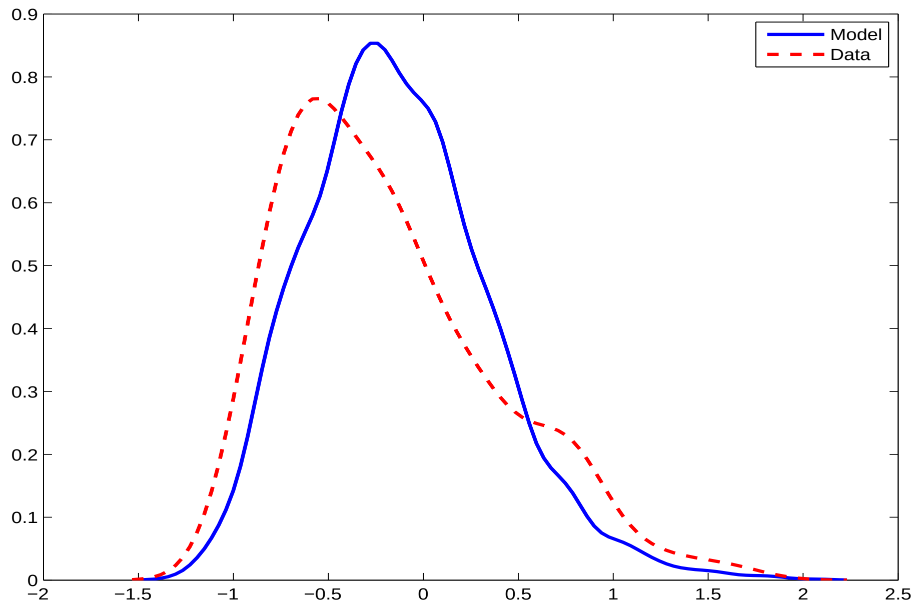


Figure B.6: Distribution of hourly earnings in agriculture: model and data

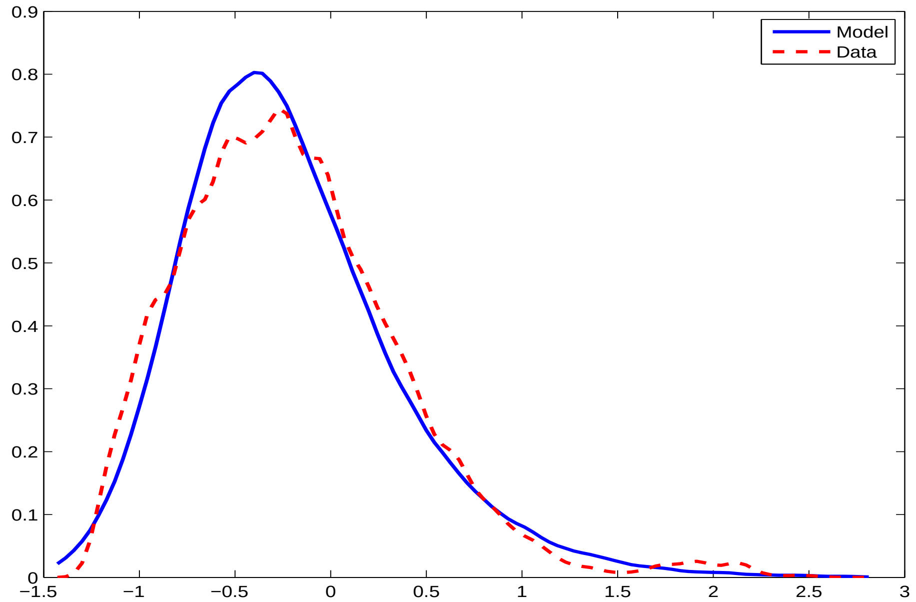


Figure B.7: Distribution of hourly earnings in non-agriculture: model and data

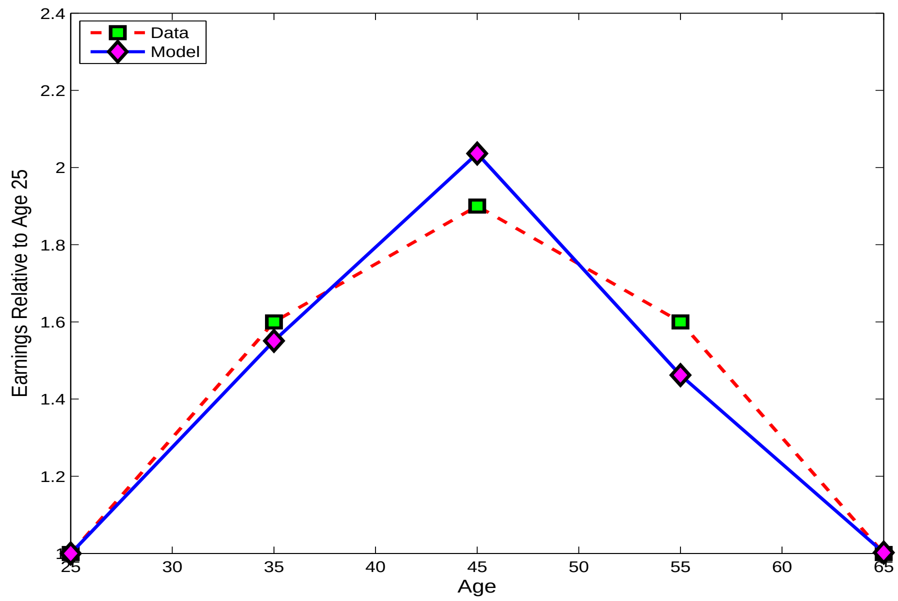


Figure B.8: Age-earnings profiles in agriculture: model and data

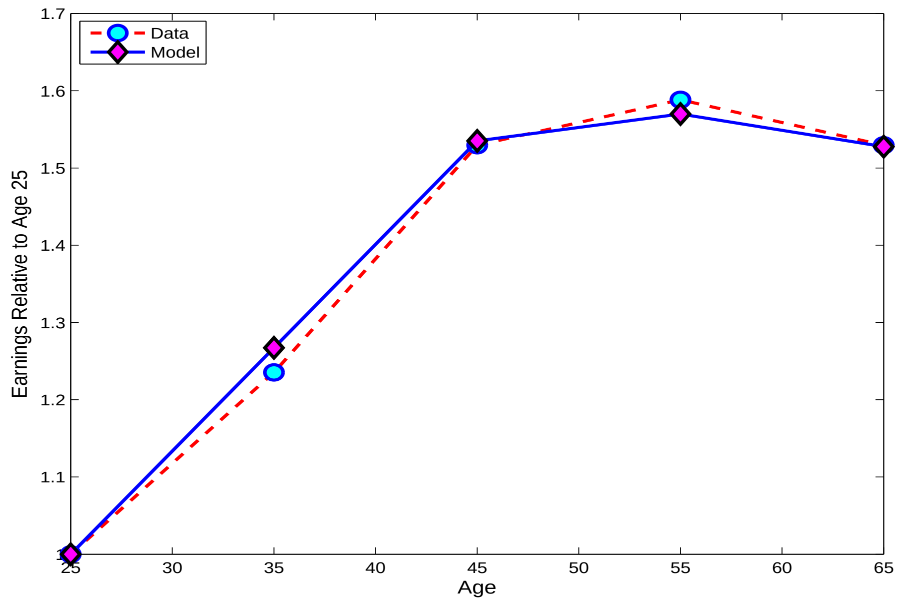
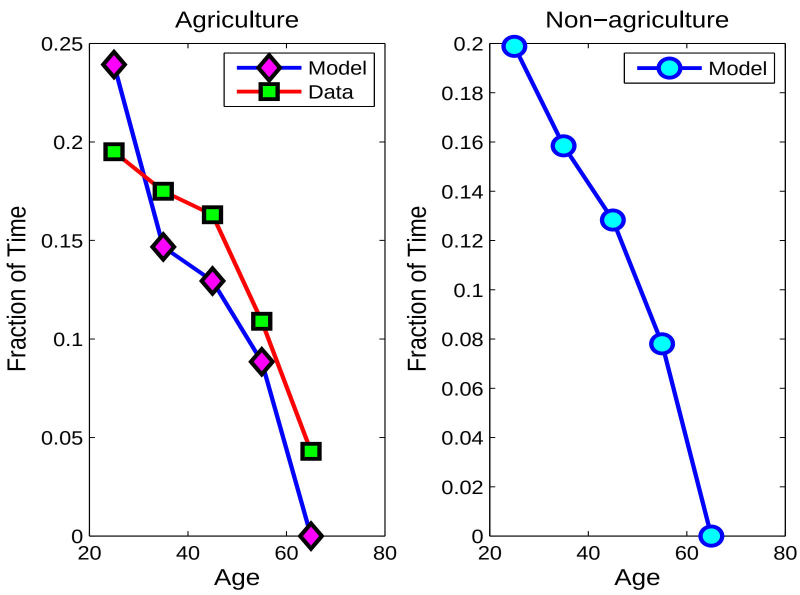


Figure B.9: Age-earnings profiles in non-agriculture: model and data



Note: Data in left panel refers to the number of days farm operators do not work on the farm, as a percentage of total working days (250). This information is calculated from 2007 census of agriculture.

Figure B.10: Time allocated to skill accumulation: model and data

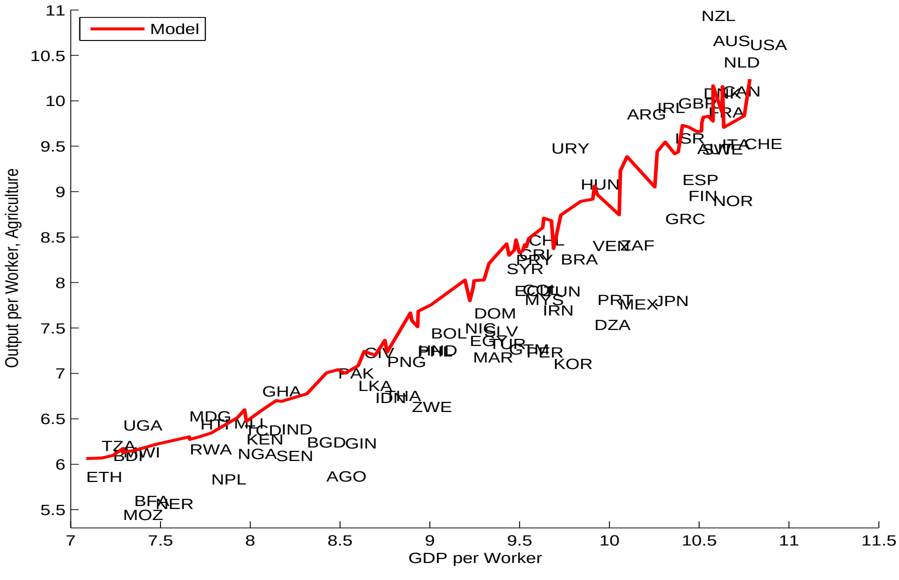


Figure B.11: Output per worker in agriculture: model and data

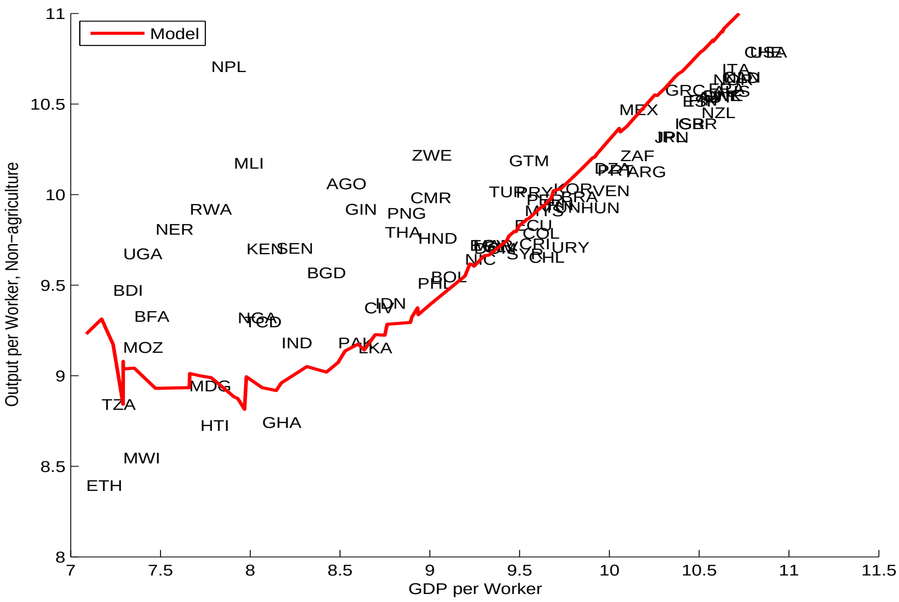


Figure B.12: Output per worker in non-agriculture: model and data

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