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Technology Adoption, Capital Deepening, and International Productivity Differences

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Abstract

Cross-country differences in capital intensity are larger in agriculture than in the non-agricultural sector. I build a two-sector model featuring technology adoption in agriculture. As the economy develops, farmers gradually adopt modern capital-intensive technologies to replace traditional labor-intensive technologies, as is observed in the U.S. historical data. Using this model, I find that technology adoption is key to explaining lower agricultural capital intensity and labor productivity in poor countries. By allowing for technology adoption, my model can explain 1.56-fold more in rich-poor agricultural productivity differences. I further show that land misallocation impedes technology adoption and magnifies productivity differences.

Keywords: Agricultural Productivity, Technology Adoption, Capital Intensity, Misallocation.

JEL classification: E13, O41, Q12, Q16.

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1 Introduction

Cross-country labor productivity differences are larger in the agricultural sector than in the non-agricultural sector. Moreover, poor countries allocate a larger percentage of employment to their agricultural sector due to low agricultural productivity and the need to meet the subsistence requirement for the agricultural good (Caselli, 2005; Restuccia et al., 2008). In this paper, I study the cross-country agricultural productivity differences through the lens of technology adoption, where rich countries mechanize their agricultural production using modern capital-intensive technology, while poor countries use less productive traditional technology with low capital intensity.

The difference in agricultural technology adoption is motivated by a new stylized fact that has not yet been explored in the literature: agricultural production in poor countries is far less capital intensive than in rich countries. I construct a new cross-country dataset on sectoral capital intensity, which can be measured by either the capital-output ratio or the capital-labor ratio. I find that capital intensity is generally lower in poor countries, and that the differences are particularly large in the agricultural sector. This indicates that rich and poor countries use different agricultural technology embedded in the capital stock, which is also confirmed by observed cross-country differences in modern machinery inputs in agriculture, such as tractors and combine harvesters.

To study changes in agricultural technology over time, I explore historical data for the United States on capital intensity and agricultural technology, covering the twentieth century. I find that although the capital-output ratio remained relatively constant in the non-agricultural sector, it increased over time in the agricultural sector. This century also saw massive mechanization of the U.S. agricultural production process, especially in the post-war period, when farmers substituted labor with tractors, harvesters, and other major machines. Motivated by these pieces of evidence, I address two research questions in this paper: why poor countries have not mechanized their agricultural production, and how differences in agricultural mechanization contribute to international differences in agricultural capital intensity and labor productivity.

I model the observed mechanization as a process of technology adoption in agriculture. I build a general equilibrium model with an agricultural sector and a non-agricultural sector, allowing for technology adoption in agriculture. Farmers choose from two technologies: a traditional labor-intensive technology with a lower capital share and a lower total factor productivity (TFP), and a modern capital-intensive technology with a higher capital share and a higher TFP. As the economy develops, capital becomes cheaper relative to labor — wage increases as labor productivity increases, while the price of capital decreases due to the improvement of investment-specific technology as in Greenwood et al. (1997). As a result, farming with modern technology becomes more profitable and the traditional technology is gradually replaced. Along with this process, agricultural labor productivity increases for two reasons. First, capital intensity increases in agriculture, which increases labor productivity. This is the capital deepening effect. Second and more importantly, there is an increase in agricultural sectoral TFP that is embedded in the capital deepening process, since the modern technology has a higher TFP than the traditional technology. As a result, the model is consistent with the data that, in the U.S., we observe rapid agricultural labor productivity growth over the twentieth century, together with an increased capital-output ratio in agriculture. It follows that, the observed cross-country variation in agricultural capital intensity can reflect underlying differences in technology adoption and the associated differences in sectoral TFP. The international differences in both capital intensity and sectoral TFP contribute to agricultural labor productivity differences.

To discipline the analysis, I calibrate this model to U.S. historical data covering the entirety of the twentieth century (1900-2000). The model successfully replicates the time series of agricultural employment share, labor productivity, capital intensity, and, in particular, the technology adoption curve as seen in the historical U.S. data. Then I use this model reflecting mechanization in the U.S., which is my benchmark, to study the lack of mechanization in the poor countries. This calibrated model allows me to identify whether the lack of mechanization in poor countries is due to their lower stages of development, or due to exogenous frictions that impede technology adoption.

I first focus on aggregate factors by measuring economy-wide TFP and barrier to investment. These aggregate factors affect both the agricultural and non-agricultural sectors and are estimated using moments from the non-agricultural sector. I also control for land and labor endowments. I then vary the model parameters to match the moments of the non-agricultural sector of the poorest countries, and use the model to generate agricultural moments. I find that these aggregate factors can explain two thirds of the observed differences between the U.S. and the poorest countries in terms of agricultural capital intensity and labor productivity. Furthermore, I find that technology adoption is crucial for the model to match the data. As I will discuss in detail later, without a technology adoption choice, the model would predict higher agricultural capital-output ratio for poor countries than for rich countries, which is opposite to what we observe in the data.

To explain the remaining portion of observed differences, I explore the role of land misallocation as a potential candidate. Recent literature emphasizes that land market misallocation is especially severe in the agricultural sector in poor countries.[1] I extend my model to include untitled land, where farmers are allocated exogenous amounts of land and land rentals among farmers are prohibited due to a lack of proper ownership. This form of land misallocation is common in less developed countries with poor institutions (Chen, forthcoming). I find that land misallocation further reduces the capital intensity and agricultural productivity. Intuitively, farming with modern technology is only profitable if farm size is large enough for farmers to use machines to replace human labor. If farmers cannot buy or rent additional land to expand their farm size, then they have less incentive to adopt the modern technology. With untitled land on top of the aggregate factor differences, the model is able to explain almost all the observed differences between the U.S. and poor countries with respect to capital intensity and 72% of the agricultural productivity differences. Furthermore, the technology adoption curve of poor countries is different from that of the U.S.

[1]See, for example, Adamopoulos and Restuccia (2014), Adamopoulos and Restuccia (2015), and Chen (forthcoming), among others.

My paper is related to the macroeconomic literature on agricultural productivity differences across countries.[2] My paper differs from existing literature in that I introduce technology adoption in agriculture to capture the phenomenon of mechanization. A closely related paper in the literature on technology adoption is Manuelli and Seshadri (2014), which finds that the diffusion of tractors in the U.S. economy can be explained in a frictionless framework by improvement in quality of tractors and in the relative price between tractors and labor. My paper differs from theirs by focusing more on a cross-country comparison of technology adoption, and studying how this can explain international agricultural productivity differences. My results are consistent with their finding that the relative price between capital and labor is important in explaining technology adoption.[3] Another closely related paper in the literature on agricultural productivity is Caunedo and Keller (2016), which finds that the quality of agricultural capital differs across countries, and that this fact accounts for 40% of agricultural productivity differences between rich and middle-income countries. By focusing on agricultural capital intensity differences across countries, my paper complements their findings on capital quality differences.[4] Caunedo and Keller (2016) further calibrate their model to exactly match the quality differences of agricultural capital

[2]See, for example, Gollin et al. (2002), Gollin et al. (2004), Gollin et al. (2007), Restuccia et al. (2008), Adamopoulos (2011), Lagakos and Waugh (2013), Gollin and Rogerson (2014), Gollin et al. (2014a), Adamopoulos and Restuccia (2014), Tombe (2015), Adamopoulos and Restuccia (2015), Donovan (2016), Gottlieb and Grobovšek (2016), and Chen (forthcoming), among others.

[3]I further model heterogeneous farmers to build a micro foundation of technology adoption, compared to the aggregate production function approach in their paper.

[4]The stylized fact of agricultural capital intensity differences holds even if capital is measured in physical quantities. Hence, the measured differences in capital intensity are not simply due to the differences in the quality of capital, as emphasised in Caunedo and Keller (2016).

across countries, while I calibrate my model to historical data of the U.S. and then use my model to explain the cross-country differences in agricultural capital quantity.[5]

My paper is also related to the literature studying long-run economic growth, in particular, the transition to the modern balanced growth path.[6] Two closely related papers are Gollin et al. (2007) and Yang and Zhu (2013). They both model the choice between a traditional technology and a modern technology in agriculture, and study how the economy converges to the modern balanced growth path. My paper differs from these works in two ways. First, my motivation for modelling technology adoption is to explain cross-country agricultural productivity differences, instead of long-run growth. Second, I model heterogeneous farmers and study technology adoption at the farm level. Modelling heterogeneity allows me to empirically match the technology adoption curve observed in the data. It also allows me to study the role of land misallocation and its negative impact on technology adoption. Hence, my paper also contributes to both the technology adoption literature and the literature studying land misallocation in agriculture.[7]

The paper proceeds as follows. Section 2 describes both cross-country and U.S. historical stylized facts on capital intensity in agriculture. Section 3 describes the

[5]My model also matches the U.S. historical data on structural transformation, capital intensity, and technology adoption.

[6]See, for example, Hansen and Prescott (2002) and Ngai (2004), among others.

[7]See, for example, Parente and Prescott (1994), Comin and Hobijn (2010), and Bustos et al. (2016) for technology adoption, and Ayerst (2016) for the impact of misallocation on technology adoption. The misallocation literature includes, for example, Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), and in particular the literature studying misallocation in agriculture includes, for example, Adamopoulos and Restuccia (2015), Adamopoulos et al. (2016), Restuccia and Santaeulàlia-Llopis (2017), and Chen et al. (2017).

model. Section 4 discusses the calibration strategy. Section 5 shows my results of the quantitative analysis. Section 6 concludes the paper.

2 Evidence on Capital Intensity

I document two stylized facts of agricultural capital intensity. First, capital intensity differences across countries are especially prominent in the agricultural sector. Second, historically in the U.S., capital intensity is seen to increase much faster in agriculture than in non-agriculture. I show that these patterns are consistent with the trend of agricultural technology adoption.

2.1 Agricultural Capital Intensity across Countries

Data.—I construct a dataset on sectoral capital intensity that are comparable across countries. I first use data from the World Bank (Larson et al., 2000), which provide estimates of capital stocks for both agricultural and non-agricultural sectors across 62 countries, covering both rich and poor ones, for the years 1967 - 1992. The capital stocks data are, however, measured in local price. To obtain real measure that is comparable across countries, I adjust for local price of capital using price data from the Penn World Table 8.0 (Feenstra et al., 2015). I next estimate the sectoral real value-added, following the procedure described in Caselli (2005) and Gottlieb and Grobovšek (2016) and combining data from two different sources: 1) data from the World Development Indicators (WDI) on nominal sectoral value-added with associated price data, and 2) data from the Food and Agricultural Organization (FAO) on real agricultural gross output with associated price data. I combine data for sectoral capital and output to calculate capital-output ratios at the sectoral level. Additionally, I calculate capital-labor ratios using employment data from the FAO and the Penn World Table 8.0. See the data appendix for a detailed description of data sources.

I also calculate sectoral capital-output ratios using the World Input-Output Database (Timmer et al., 2015). This database provides a balanced panel of capital-output ratios across countries, which is suitable for regression analysis. The problem of this dataset is, however, that it mainly covers rich and middle-income countries, while my dataset has better coverage of poor countries. Hence, I only use the WIOD data as a robustness check.

International patterns of capital intensity.—It is well-known that, relative to rich countries, poor countries have lower capital intensity, measured as real capital-output ratio or capital-labor ratio (Hsieh and Klenow, 2007).[8] What is less well-known is that these differences are larger in the agricultural sector than in the non-agricultural sector. The upper panels of Figure 1 shows the real capital-output ratio and capital-labor ratio across countries, for both the agricultural and non-agricultural sectors. The figure illustrates the first stylized fact: richer countries have higher capital-output ratio and capital-labor ratio in both sectors, but the differences in agriculture are much larger. For example, the non-agricultural capital-labor ratio differs by around 10-fold between

[8]In cross-country analysis, *real* means that capital and output are measured using common international prices, while *nominal* means they are measured in local prices. This is in contrast to the time series analysis in the next stylized fact, where *nominal* means that capital and output are measured using current prices instead of constant prices.

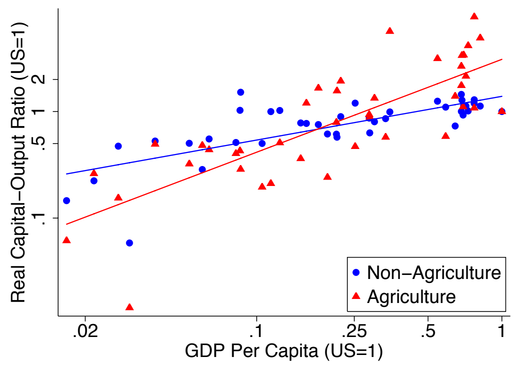
the U.S. and the 20% poorest countries in my sample, while the agricultural capital-labor ratio differs by 165-fold.[9] Note that this fact is not driven by the price deflators since it also holds if we compare nominal capital-output ratio, measured using local prices, across countries. The bottom panel of Figure 1 shows that, while the nominal capital-output ratio in the non-agricultural sector is roughly the same across countries, it differs substantially in the agricultural sector.

I further confirm this stylized fact in a cross-country regression using both my constructed data and the WIOD data. Let $\Delta\frac{K}{Y} = \log\frac{K_a}{Y_a} - \log\frac{K_n}{Y_n}$ denote the difference of capital-output ratios between agriculture and non-agriculture within a country, measured either in nominal or real terms. I regress this variable on countries' real GDP per capita, time dummies, and country dummies. The results are displayed in Table 1: the capital-output ratio of agriculture increases with GDP per capita *relative to* that of the non-agricultural sector, under both nominal and real measures, consistent with Figure 1. Therefore, it is a robust fact that the cross-country differences of capital intensity are larger in agriculture than in the non-agricultural sector.

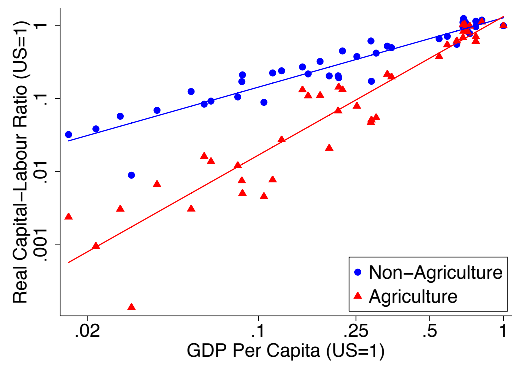
This fact is consistent with evidence in international differences in agricultural technology from the Cross-Country Historical Adoption of Technology (CHAT) data set (Comin and Hobijn, 2004). According to the CHAT dataset, the aforementioned 20% poorest countries in my dataset have on average only 1.40 tractors per 1000 hectares, compared to 10.96 tractors in the U.S. Similarly, agricultural harvester machines also

[9] The 20% poorest countries in my sample are El Salvador, Malawi, Tanzania, Madagascar, India, Kenya, Egypt, and Pakistan, sorted by their real GDP per capita.

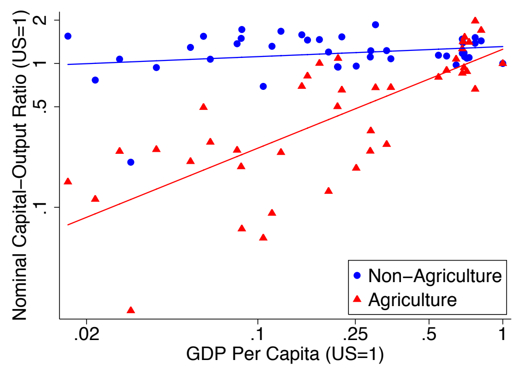
Figure 1: The Capital Intensity across Countries



(a) Real Capital-Output Ratio



(b) Capital-Labor Ratio



(c) Nominal Capital-Output Ratio

Note:

[1] All variables are normalized relative to the U.S. and are in log scale.

[2] In Figure (a) and (b), capital and output are both real measures, adjusted by their price deflators across countries. In Figure (c), Capital and output are nominal measures with local prices.

[3] The slopes of the fitted lines in Figure (a) are 0.87 and 0.41 for agriculture and non-agriculture, respectively. The corresponding numbers are 1.90 and 0.95 in Figure (b), and 0.69 and 0.07 in Figure (c).

Table 1: Capital-output Ratio across Countries

Dep. Var. ($\Delta K/Y$)	Constructed Dataset (1)	(2)	(3)	(4)	WIOD Data (5)	(6)
Log GDP	0.66	0.31	0.43	0.56	0.41	0.19
	(0.03)	(0.09)	(0.03)	(0.07)	(0.03)	(0.14)
Time FE		✓		✓		✓
Country FE		✓		✓		✓
$\Delta K/Y$ Measure	Nominal	Nominal	Real	Real	Nominal	Nominal

Note:
[1] The data are from the World Bank (Larson et al., 2000) and the World Input-Output Database (Timmer et al., 2015).
[2] I regress $\Delta\frac{K}{Y}$ ($\log(\frac{K_a}{Y_a}) - \log(\frac{K_n}{Y_n})$) on log GDP per capita (PPP), country dummies and time dummies. Standard errors are in bracket.
[3] Nominal measure means capital and output are measured using local price; real measure uses international comparable prices.

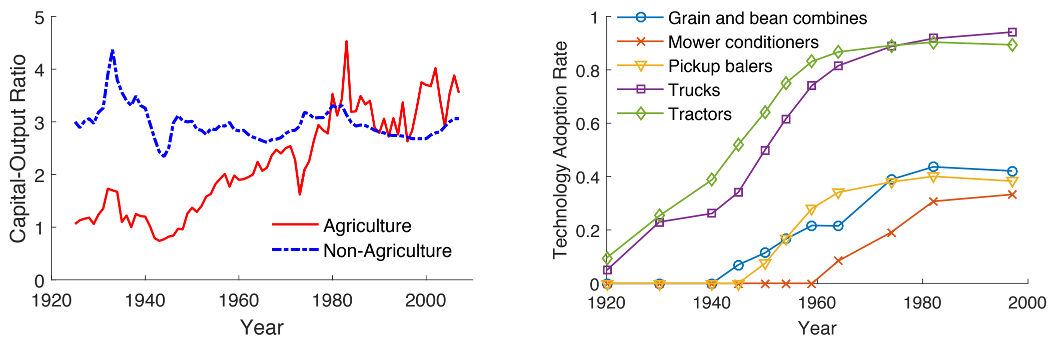
differ by around 14-fold. Therefore, rich and poor countries differ in the organization of agricultural production, as reflected by differences in agricultural capital intensity and usage of modern machinery inputs.

2.2 U.S. Agricultural Capital Intensity over Time

The second stylized fact is that, in the United States, capital intensity increases faster in the agricultural sector than in the non-agricultural sector in the twentieth century. The left panel of Figure 2 shows the capital-output ratio in the U.S. of both agricultural and non-agricultural sectors, which are from the U.S. Bureau of Economic Analysis (BEA).[10] We can see that while the capital-output ratio (measured in current prices) is stable in the non-agricultural sector, consistent with the Kaldor facts, it increases over time in the agricultural sector. The increasing agricultural capital intensity comes from

[10] Note that the data from the BEA have already account for quality improvements. See Chapter 4 of the National Income and Product Accounts (NIPA) Handbook.

Figure 2: The Capital-Output Ratio in the U.S.



Note:
[1] The left figure shows the capital-output ratio in the U.S. measured using current prices and the data are from the U.S. Bureau of Economic Analysis (BEA).
[2] The right figure shows the percentage of agricultural output produced by farms with modern machinery, calculated using data from the U.S. census of agriculture.

the postwar period of mechanization in the U.S. agricultural sector. The right panel of Figure 2 shows the percentage of agricultural output produced by farms with modern machinery, such as trucks, tractors, and combines, in the U.S. starting from 1920. Machinery usage increases rapidly between 1940 and 1980, which is also the period that agricultural capital intensity increases relative to the non-agricultural sector.[11]

3 A Model with Technology Adoption

I present a two-sector neoclassical growth model featuring technology adoption in agriculture. I describe the model in two steps. First, I consider a static problem where farmers choose between different technologies taking prices as given. Second, I close the model by introducing the dynamic general equilibrium with two sectors, where I lay

[11] Manuelli and Seshadri (2014) provides an excellent discussion on how tractors replace horses and human labor in agricultural production, in response to the drop in relative price of tractors versus other inputs.

out the market structure and the representative household's problem on consumption and investment, as well as labor supply to both sectors.

3.1 Farmers' Problem

I start by describing the farmer's choice problem between different technologies, taking prices as given. This problem helps us understand the process of technology adoption, which is a key component of my model. Since this problem is static, I omit the time subscript t to simplify notation.

There is a measure N_a of farmers in the economy, who can produce the agricultural good on their farms and sell it at price p. Each farmer operates one farm, and is endowed with one unit of labor in each period and supplies it inelastically to the farm. Farmers differ in their farming ability $s \in F(s)$. This ability can be interpreted as knowledge of crop cultivation, managerial talent of the farming business, or even the physical strength.

3.1.1 Traditional and Modern Technologies

The agricultural good can be produced using two alternative technologies: a traditional technology that is less capital intensive and a modern technology that is more capital intensive. Consider a farmer with ability s. He can operate a farm with the traditional technology given by

$$y = A\kappa s^{1-\alpha_r-\gamma_r} k^{\alpha_r} l^{\gamma_r},$$

where y is the farm's output, A is the economy-wide productivity, κ is the agricultural-specific productivity (such that A and κ are common to all farms), k and l are the capital and land inputs of the farm, and α_r and γ_r are the capital and land shares of the traditional technology. Following Adamopoulos and Restuccia (2014) and Chen (forthcoming), I assume that farms use labor input from the farmer only, which is s in efficiency units, and does not hire any off-farm labor.[12] The profit of operating a traditional farm is given by

$$\pi_r(s) = \max_{\{k,l\}}\{pA\kappa s^{1-\alpha_r-\gamma_r}k^{\alpha_r}l^{\gamma_r} - p^k rk - ql\},$$

where r and q are the rental rates of capital and land, and p^k is the price of the capital good.

The farmer can also operate a farm with modern technology given by

$$y = AB\kappa s^{1-\alpha_m-\gamma_m}k^{\alpha_m}l^{\gamma_m},$$

where α_m and γ_m are the capital and land shares of the modern technology, and B measures the relative productivity difference between the traditional and the modern technologies.[13] I assume $\alpha_m > \alpha_r$ since modern technology is more capital intensive. It is then natural to assume that the traditional technology is more labor and land

[12] I focus on family farms and abstract from hiring labor decision, following the literature. In the data, labor hired by farms is usually difficult to measure due to issues such as unauthorized labor. Furthermore, evidence suggests that hired labor is relatively limited in quantity compared to family labor: Adamopoulos and Restuccia (2014) show that, among 55 countries over the world, each farm on average uses 5.26 household member workers, and only 0.2 outside-hired workers who work more than 6 months of the year.

[13] Technically, $B = B_1 \cdot B_2$, where B_1 is a scaling constant (which is necessary since the two technologies have different factor shares and are therefore not unit-free), while B_2 measures the difference of productivity between the two technologies. As a result, $B = 1$ does not necessarily mean that the two technologies have the same productivity.

intensive, which implies $\gamma_m < \gamma_r$ and $1 - \alpha_m - \gamma_m < 1 - \alpha_r - \gamma_r$. The profit of operating a modern farm is given by

$$\pi_m(s) = \max_{\{k,l\}} \{pAB\kappa s^{1-\alpha_m-\gamma_m} k^{\alpha_m} l^{\gamma_m} - p^k rk - ql\}.$$

Choosing the modern technology incurs a fixed cost of f units of capital good in every period. This fixed cost can be interpreted as indivisibility of equipment, up-front investment in learning, or the required infrastructure of modern technology. This assumption of fixed cost associated with technology choice is widely used in the literature, such as Helpman et al. (2004) and Adamopoulos and Restuccia (2015). Sunding and Zilberman (2001) survey literature studying technology adoption in agriculture, and find that this fixed cost assumption does capture the salient features of agricultural technology adoption observed in the data. I model this fixed cost as a per period cost, but we can also view it as a one-time up-front fixed cost that is financed over multiple periods.[14]

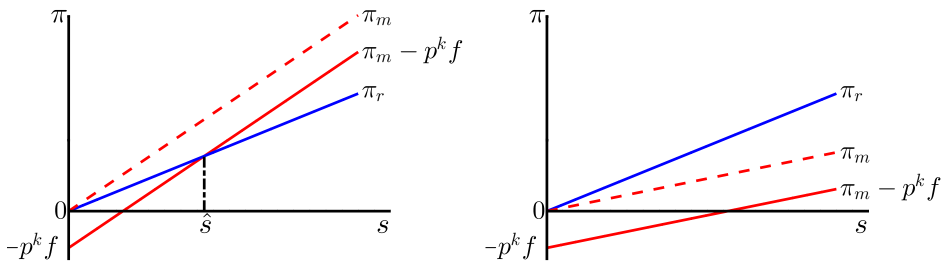
3.1.2 Technology Choice

A farmer with ability s will choose the modern technology if and only if the profit from using the modern technology exceeds that of using the traditional technology by at least the value of the fixed cost:

$$\Delta\pi(s) = \pi_m(s) - \pi_r(s) \geqslant p^k f. \tag{1}$$

[14] As will be clear later, since there is no financial friction or uncertainty in this model, these two setups are equivalent.

Figure 3: Technology Choice



The difference in profits is linear in the farmer's ability s: $\Delta\pi(s) = \pi^m(s) - \pi^r(s) = s\Omega(p, q, r, p^k)$, where Ω is a function of prices independent of s. Therefore, Equation (1) can be rewritten as

$$\Delta\pi(s) = s\Omega \geqslant p^k f. \tag{2}$$

There are two possible scenarios associated with technology adoption. Scenario (1): $\Omega > 0$, so that $\pi_m(s) - \pi_r(s) = s\Omega > 0$ for any farmer. I plot this scenario in the left panel of Figure 3, where the profit functions are plotted against farmer ability. Modern technology is potentially more profitable than traditional technology for all farmers (the line of π_m is always above the line of π_r), but the fixed cost reduces the actual payoff of the modern technology (the line of π_m shifts down to $\pi_m - p^k f$). As a result, only high-ability farmers whose farms are large enough can afford the fixed cost and adopt the modern technology. Let us denote the cut-off ability as $\hat{s}$ such that, given the fixed cost, a farmer with $s = \hat{s}$ is indifferent between the two technologies. This requires $\hat{s}\Omega = p^k f$, or $\hat{s} = \frac{p^k f}{\Omega}$. All farmers above this threshold ($s \geqslant \hat{s}$) choose modern technology, and farmers below it choose traditional technology. Scenario (2): if $\Omega < 0$, then Equation (2) can never be satisfied and the modern technology will not be adopted by any of the farmers. This scenario is illustrated in the right panel of Figure 3.

3.2 Dynamic General Equilibrium

Having described the farmers' problem, I close the model by introducing a simple two-sector dynamic general equilibrium.

3.2.1 Two Sectors

There are two sectors in this economy: an agricultural sector and a non-agricultural sector. In the agricultural sector, farmers of heterogeneous ability produce the agricultural good on their farms as described before. The agricultural good is priced at p_t and is used for consumption only.

In the non-agricultural sector, there is a representative firm that employs capital $\tilde{K}_{nt}$ and labor $\tilde{N}_{nt}$ to produce the non-agricultural good Y_{nt}:

$$Y_{nt} = A_t \tilde{K}_{nt}^{\alpha_n} \tilde{N}_{nt}^{1-\alpha_n},$$

where A_t is the economy-wide TFP (common to both agriculture and non-agriculture), and α_n is the capital share in the non-agricultural sector. Let the non-agricultural good be the numeraire with its price normalized to one.

The non-agricultural good can either be used for consumption or transformed into capital through a linear technology, following Greenwood et al. (1997). Let υ_t denote this investment-specific technology: 1 unit of non-agricultural good can be transformed into υ_t units of capital good. Therefore, the price of capital good is given by $p_t^k = \frac{1}{\upsilon_t}$.

3.2.2 The Representative Household's Problem

There is a measure one of infinitely-lived representative household in this economy. This household has N_t members in period t and grows at a rate of n. Each household member is endowed with one unit of time in each period that is supplied inelastically to the labor market. The household allocates N_{at} of its members to be farmers in the agricultural sector and the remaining $N_{nt} = N_t - N_{at}$ to be workers at the representative firm in the non-agricultural sector. Farmers are heterogeneous in their farming ability s and each earn farming profit $\pi(s)$. Workers are, however, homogeneous and earn the same wage w subject to a tax rate ξ. I use this tax to capture the labor mobility barrier between sectors, which is also used in Adamopoulos and Restuccia (2014) and Chen (forthcoming). I will discuss this barrier in detail in the calibration. The tax revenue is rebated to the household so it does not affect aggregate demand. The total household labor income is given by

$$N_{nt} w_t (1 - \xi) + N_{at} \int_{s \in S} \pi_t(s) F(ds),$$

where the first term represents income from workers and the second term is that from farmers.

I follow Adamopoulos and Restuccia (2014) in abstracting from selection in occupational choice. In other words, the household only determines the fraction of its members working in agriculture without selecting on the basis of ability. This assumption keeps the distribution of farmer ability constant across time and across country. Lagakos and Waugh (2013) study self-selection in depth and show that it aggravates agricultural productivity differences across countries. Since selection is well understood in the literature, I abstract from it in this paper to keep my model tractable.[15]

The household derives its utility from consuming both the agricultural good and the non-agricultural good:

$$U = \sum_{t=0}^{\infty} \beta^t \big[\phi \log(c_{at} - \bar{a}) + (1-\phi)\log(c_{nt})\big] N_t,$$

where β is the discount factor, ϕ is a preference weight of the agricultural good, and $\bar{a}$ is a subsistence requirements for agricultural consumption. Consumption of each good in period t is denoted by c_{at} and c_{nt}, respectively. The household's total income is the sum of labor income, capital income, and land income:

$$(N_t - N_{at})w_t(1-\xi) + \int_{s\in S} \pi_t(s)F(ds)N_{at} + p_t^k r_t k_t + q_t L + T_t, \quad \forall t.$$

where L and k_t are total household land endowment and capital stock, and T_t is the household rebate from labor income tax which equals $(N_t - N_{at})w_t\xi$ in equilibrium. This household divides its total income into consumption $(p_t c_{at} + c_{nt})N_t$ and investment $p_t^k x_t$ in each period t. The investment expenditure increases the capital stock for the next period:

$$k_{t+1} = (1-\delta)k_t + \frac{x_t}{\eta}.$$

Here η is the barrier to investment: I follow Ngai (2004) and Restuccia (2004) by assuming that one unit of investment increases capital stock by $\frac{1}{\eta}$ units. Therefore, this parameter η captures the distorted prices for capital typically observed in poor

[15] Note that although there is no selection in occupational choice, there is selection in technology adoption choice among farmers.

countries (Restuccia and Urrutia, 2001).[16]

3.2.3 Equilibrium and Characterization

I focus on the competitive equilibrium for this economy, which is defined in Appendix A.1. Although this model may seem complex, its dynamic properties are similar to a standard one-sector neoclassical growth model. In Appendix A.2, I show how the model can be aggregated. The aggregate growth of my model is similar to that of the neoclassical growth model, with two distinct features in the long-run growth. First, with economic development, there will be ongoing structural transformation, where employment is reallocated from the agricultural sector to the non-agricultural sector: as labor productivity improves in the agricultural sector, fewer resources are required to produce the subsistence requirement $\bar{a}$ (Kongsamut et al., 2001; Herrendorf et al., 2014).[17] Second, the investment-specific technology υ_t plays a larger role in my model than in the standard neoclassical growth model. In the neoclassical growth model, the economy-wide TFP and the investment-specific technology have similar impact on labor productivity. In my model, however, an improvement in υ reduces the cost of capital and benefits farmers with modern technology more than farmers with traditional technology, thus promoting technology adoption. This is in contrast with economy-wide TFP, which affects farmers neutrally, regardless of technology choice.

[16] Technically, a change in η is similar to a change in the level of $\{\upsilon_t\}_{t=0}^{\infty}$ in affecting the cost of capital. Later in the quantitative analysis, I assume that the investment-specific technology $\{\upsilon_t\}_{t=0}^{\infty}$ is common to all countries, while this barrier η is country-specific and time-invariant.

[17] I follow this literature of structural change by assuming there is no trade in the agricultural good, consistent with evidence from Tombe (2015).

4 Calibration

4.1 Parameters and Targets

I calibrate my model to historical data of the U.S. economy encompassing the entire twentieth century (1900 to 2000). This century saw impressive mechanization in the agricultural sector of the U.S. economy. During this period, the price of capital decreased relative to labor, and capital-output ratio increased in the agricultural sector but barely changed in the non-agricultural sector. The historical data for this period provide information on the prevalence of modern technology adoption given prices, productivity changes, and capital intensity changes in agriculture. Therefore, I use historical data to calibrate my model, in particular, to restrict parameters determining technology adoption. The data appendix describes in detail the historical data used in my calibration.

4.1.1 Time-Invariant Parameters

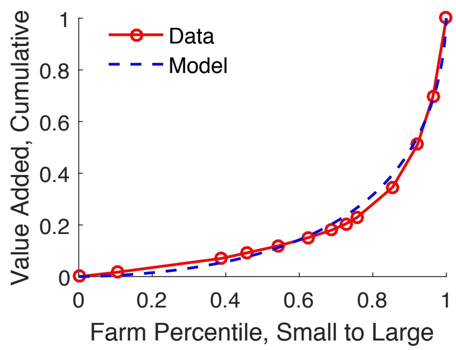
Some parameters of the model are time-invariant, while others have a time series of values that change over time. Let me begin by describing how I choose the values of the 12 parameters that are time-invariant, consisting of five parameters determining factor shares $(\alpha_r, \gamma_r, \alpha_m, \gamma_m, \alpha_n)$, three parameters determining household's preferences $(\phi, \bar{a}, \beta)$, the barrier to labor mobility ξ, the depreciation rate δ, the barrier to investment η, and one parameter governing the farmer ability distribution $F(s)$. Eight of them $(\alpha_r, \gamma_r, \alpha_m, \gamma_m, \alpha_n, \delta, \eta, \xi)$ are directly assigned values that are either common in the literature or from moments that do not depend on the equilibrium. The other four are calibrated by comparing the model's equilibrium moments with data.

Factor Shares: $\alpha_r, \gamma_r, \alpha_m, \gamma_m, \alpha_n$.—I choose the parameters of the technologies such that the factor shares are consistent with estimations in the literature. I set $\alpha_m = 0.36$ and $\gamma_m = 0.18$. As a result, the capital, labor, and land shares associated with modern technology are 0.36, 0.46, and 0.18, respectively, consistent with Valentinyi and Herrendorf (2008). I set $\alpha_r = 0.1$ and $\gamma_r = 0.25$ such that the capital, labor, and land shares associated with traditional technology are 0.10, 0.65, and 0.25, respectively, similar to Caselli and Coleman (2001) and Gollin et al. (2007). Note that the key assumption of capital deepening ($\alpha_m > \alpha_r$) is satisfied in the calibration. The capital share associated with the non-agricultural sector, α_n, is set to 0.33 following Gollin (2002).

Preferences: $\phi, \bar{a}, \beta$.—Two preference parameters ϕ and $\bar{a}$ govern the agricultural employment share. In particular, when an economy is still in its early stages of development and agricultural productivity is low, agricultural employment share is mainly determined by $\bar{a}$. The term ϕ then determines agricultural employment share when the economy converges to the asymptotic balanced growth path. I choose the values of these two parameters such that, given agricultural labor productivity for each of 1900 and 2000, agricultural employment share is 33.97% for the year 1900 and 1.48% for 2000 to match the data. I set the discount rate β to 0.96 to match an average capital-output ratio of 3 in the non-agricultural sector.

Ability Distribution.—I assume that farmer ability follows a lognormal distribution, with mean normalized to 0 and standard deviation of σ_s. I choose the dispersion

Figure 4: Ability Distribution



Note: This graph compares the distribution of farm output generated by the model with the data. The data are obtained from Table 58 of the U.S. Census of Agriculture, which sorts farms into different bins according to their size, and calculates the value-added, which corresponds to output in my model, of farms within each bin.

parameter $\sigma_s = 1.33$ such that, once all farmers adopt modern technology, the distribution of farm output by farm size best matches the data in the 2007 U.S. Census of Agriculture. Figure 4 shows that the distribution of farm output in the calibrated model matches the data well.

Barrier to labor Mobility: ξ.—As is well-known for the U.S., the *nominal* labor productivity of the non-agricultural sector is much higher than that of the agricultural sector. This phenomenon is often referred to as the nominal agricultural productivity gap (Gollin et al., 2014b). For example, during the years 1990 - 2000, the relative productivity of non-agriculture (versus agriculture) is on average 1.68. In my model, however, if labor is perfectly mobile between sectors, the relative labor productivity is $\frac{1-\alpha_r-\gamma_r}{1-\alpha_n} = 0.90$ before technology adoption starts and $\frac{1-\alpha_m-\gamma_m}{1-\alpha_n} = 0.69$ after adoption is completed, both of which are considerably smaller than 1.68. To reconcile the relative labor productivity of the model with that of data, I introduce a barrier to labor mobility between sectors: working in the non-agricultural sector is subject to a wage tax rate

Table 2: Summary of Calibration

Parameter		Moment	Parameter		Moment
α_r	0.10	Capital share (traditional)	α_m	0.36	Capital share (modern)
γ_r	0.25	Land share (traditional)	γ_m	0.18	Land share (modern)
α_n	0.33	Capital share (non-agr.)	δ	0.04	Depreciation
η	1	Normalization	β	0.96	K/Y ratio (non-agr)
$\bar{c}$	0.055	Agr. employment (%, 1900)	ϕ	0.003	Agr. employment (%, 2000)
σ_s	1.327	Farm size distribution (2007)	ξ	0.59	Labor productivity gap

ξ. I choose ξ to match the 1.68-fold gap of nominal labor productivity for the years 1990 - 2000, when technology adoption is roughly completed. This requires $\xi = 1 - 0.69/1.68 = 0.59$. Note that although this nominal labor productivity gap between sectors is wider in earlier periods, it turns out that a constant ξ successfully reconciles the gap for the whole historical period (see Figure 7). In other words, my model can endogenously generate the nominal productivity gap that narrows over time. This is because the gap is equal to $1/(1-\xi)$ multiplied by the ratio of agricultural labor share to non-agricultural labor share (Herrendorf and Schoellman, 2015), and agricultural labor share associated with traditional technology is higher than that of modern technology. Therefore, along with technology adoption, labor share decreases in agriculture and the nominal productivity gap narrows as observed in the data. Further note that this barrier ξ is also held constant in the cross-country analysis.

Other Parameters: δ, η.—I follow the literature and set the depreciation rate of capital δ to be 0.04. The barrier to investment η is normalized to 1 in the benchmark calibration. Table 2 summarizes the values of time-invariant parameters as well as the main targets for calibration.

4.1.2 Time Series

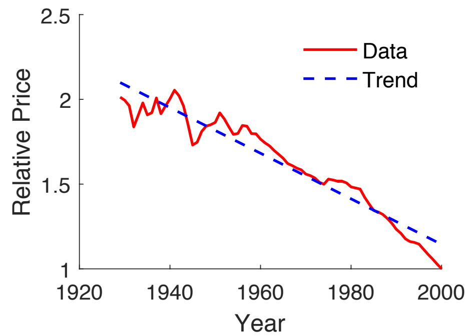
On top of these time-invariant parameters, we also need to calibrate seven time series parameters: the endowments of land and labor $\{N_t, L_t\}$, the investment-specific technology $\{\upsilon_t\}$, the economy-wide and agriculture-specific TFP $\{A_t, \kappa_t\}$, the relative productivity between traditional and modern technologies $\{B_t\}$, and the fixed cost of adoption $\{f_t\}$. Note that I use time subscripts t with curly braces to signify time series, to differentiate them from the previous 12 time-invariant parameters. For each time series, we need to determine the level and pattern of growth using historical data.

Endowments: $\{N_t, L_t\}$.—Endowment values are taken directly from the data. Total land size is rather stable over time, so I normalize $L_t = 1$ for all t. I normalize population size to 1 for the year 2000, and set the annual population growth rate to be 1.32%, consistent with the population data.

Investment-Specific Technology: $\{\upsilon_t\}$.—The investment-specific technology governs the price of the capital good (p^k). Following Greenwood et al. (1997) and Gort et al. (1999), I measure the relative price of investment and durable goods to that of consumption non-durable goods and services, using historical price data from the Bureau of Economic Analysis.[18] Note that the price series from the BEA already take into account the necessary adjustment for quality improvements of capital goods. I normalize the level of υ_t to be 1 for the year 2000, and choose the sequence such that the implied price series $\{p_t^k\}$ decreases over time in a linear pattern as shown in Figure

[18] BEA also report price data for each sector separately. Since I assume capital is homogeneous between sectors, I use the aggregate price data for both sectors. The trends of price are similar between the agricultural and the non-agricultural sectors.

Figure 5: Relative Price of Capital Goods



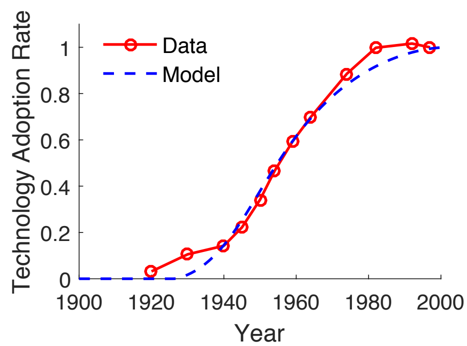
Note:
[1] The red curve shows the relative price of investment and durable goods over consumption non-durable goods and services. The data of price series are from the Bureau of Economic Analysis (BEA) tables. The price is normalized to one for the year 2000.
[2] The blue dashed line is fitted the linear trend of the data, and is used in my calibration.

5. Note that price data are only available after 1929. I extrapolate this price series back to 1900 with the assumption that 1900 - 1929 prices change in the same pattern as observed for 1929 onwards. The results are rather insensitive to the extrapolation method of pre-1929 prices, as this period saw little technology adoption in agriculture. Without technology adoption, the change in the TFP (A) and the change in the investment-specific technology (υ) have similar impact on labor productivity, as discussed in Section 3.2.3.

Productivity: $\{A_t, \kappa_t\}$.—The economy-wide TFP $\{A_t\}$ and agriculture-specific TFP $\{\kappa_t\}$ are determined in the equilibrium and are chosen to match sectoral labor productivity over time. I normalize the level of $\{A_t\}$ and $\{\kappa_t\}$ to 1 for the year 2000. I assume they grow at constant rates. The growth rate of $\{A_t\}$ is chosen to be 1% per year such that non-agricultural labor productivity increases 6.9-fold between 1900 and 2000. In contrast, agricultural labor productivity increases 30.4-fold over the same period. While technology adoption in my model implies extra growth in agricultural labor productivity, it can only account for a portion of the disparity in labor productivity increase between sectors. The remaining is captured by the growth of $\{\kappa_t\}$, which is around 1% per year. For example, the channel of self-selection can generate the pattern that labor productivity grows faster in agriculture than in non-agriculture over time (Lagakos and Waugh, 2013; Young, 2014). Although this channel is not explicitly modelled, it is captured by the growth of $\{\kappa_t\}$.

Technology Adoption.—Before we can calibrate the fixed cost of adopting the modern technology $\{f_t\}$ and the relative productivity between modern and traditional technologies $\{B_t\}$, let me briefly describe the technology adoption curve. The adoption curve is defined as a time series indicating the percentage of output produced by farms with modern technology at each period. In the data, there is no indicator variable differentiating farms using modern versus traditional technology. As a proxy, I treat farms with modern machinery as farms with modern technology. The U.S. Census of Agriculture records five kinds of modern machines over time: tractors, trucks, combines, mower conditioners, and pickup balers. I construct, for example, a time series of the percentages of output produced by farms with tractors in each year. I then normalize the value to 100% for the year 2000 and scale the pre-2000 values accordingly. This time series would represent the adoption curve of tractors. I replicate it for the other four machines, and then take the average of these five adoption curves as my technology adoption curve for the calibration, which is shown in Figure 6. See the data appendix for details. Note that in the data we also observe the pattern that

Figure 6: Technology Adoption Curve



Note: The technology adoption rate of the model is the percentage of output produced using modern technology; the rate in the data is the average percentage of output produced by farms with modern machines. See the text for a detailed description.

larger farms adopt modern technology earlier, consistent with the model's prediction.

Now, let us determine the last two series, which are also determined in the equilibrium: $\{f_t\}$ and $\{B_t\}$. To reduce the number of free parameters, I restrict the growth rates of these two series to be constant over time, so we only need to determine their levels and growth rates (four parameters in total). These four parameters are chosen such that the technology adoption curve in my model best matches that of the data (see Figure 6). The values for best fit are $f_{1990} = 0.75$ decreasing at 3.7% per year, and $B_{1900} = 2.2$ increasing at 0.1% per year. Although the magnitude of $\{f_t\}$ has little intuition, we can tell that it is not sizeable: for example, in the year 1950 when technology adoption is rapid, the fixed cost constitutes on average 4.8% of farming output among farmers using modern technology. The level of $\{B_t\}$ cannot be interpreted directly, either, since it includes a scaling constant that makes the two technologies comparable. The growth of $\{B_t\}$ is, however, more intuitive: $\{B_t\}$ increases over time, indicating that the productivity of the modern technology increases faster than that of the traditional technology. Note that $\{f_t\}$ and $\{B_t\}$ can be separately identified since the fixed cost $\{f_t\}$ is the same for every farm that adopts modern technology, while relative productivity $\{B_t\}$ affects farms proportionally based on farm size. It follows that, the technology adoption of large farms depends more on $\{B_t\}$, while that of smaller farms is more sensitive to $\{f_t\}$.

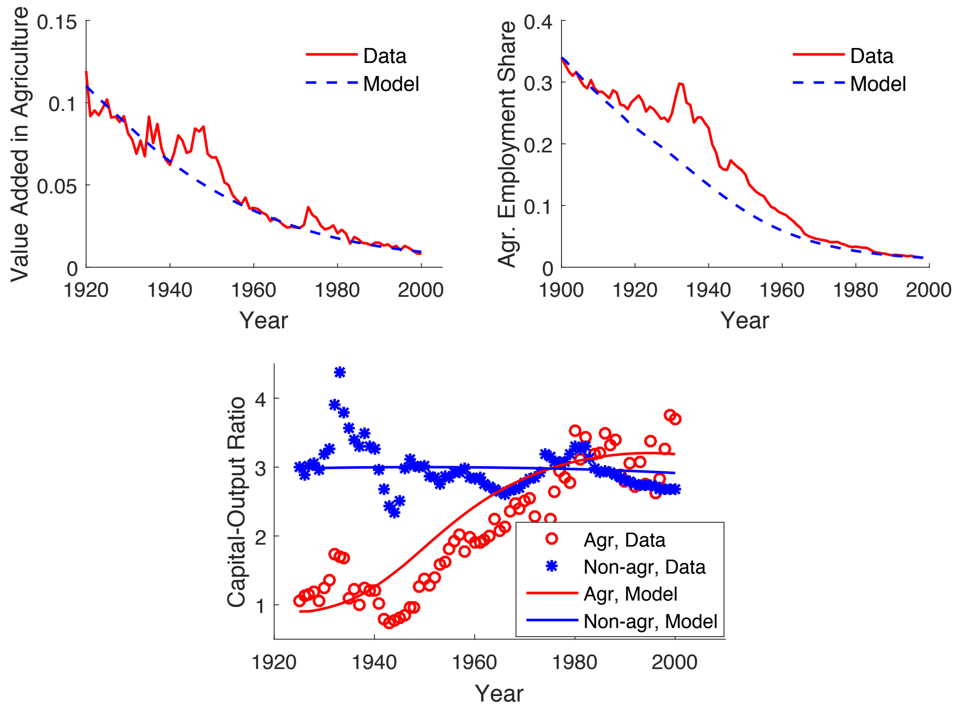
4.2 Model Fit and Discussion

The calibrated model successfully replicates the historical mechanization process of the U.S. as well as its long-run growth. Moreover, the model is also able to match other moments which are important in long-run growth, despite the fact that they are not directly targeted in the calibration. The top panel of Figure 7 shows that the model generates the same pattern of structural transformation, which can be measured either as sectoral value-added share or employment share, as seen in the data, although I only target the agricultural employment share at the beginning and end of this period.[19] The bottom panel of Figure 7 shows that the model is also capable of replicating the sectoral capital-output ratio over time, measured in current price. In particular, the model clearly replicates the capital deepening process in agriculture. Note that I do not explicitly target the capital-output ratio in the agricultural sector; it is the technology adoption channel that accounts for this capital deepening process.[20] At the sectoral level, my model implies that capital and labor are more substitutable than Cobb-

[19]The employment share in the data is a bit higher than in the model during the 1930s and 1940s, likely due to the Great Depression and World War II, which are not in my model.

[20]I target the adoption cost $\{f_t\}$ and the disparity of productivity between modern and traditional technologies $\{B_t\}$ in the calibration; neither directly affect capital intensity in agriculture.

Figure 7: Model V.S. Data – Structural Transformation



Note: The top figures compare the model's prediction on two measures of structural transformation with the data. The bottom figure compares the model's prediction on capital-output ratio with the data. These series are not directly targeted in the calibration.

Douglas in agriculture, consistent with Herrendorf et al. (2015) and Alvarez-Cuadrado et al. (forthcoming).

In the calibrated economy, modern technology gradually replaces traditional technology over time for three reasons. First, as the economy-wide TFP and investment-specific technology grows over time, wage increases 6.9-fold relative to the non-agricultural good (the numeraire) while the price of capital decreases 2.3-fold, as observed in the data. Hence, the relative price between capital and labor decreases more than 15 times in the sample period, making the modern technology more profitable. This echoes the finding in Manuelli and Seshadri (2014) that relative prices play an important role in the diffusion of tractors in the U.S. economy. Second, with structural transformation, the number of farmers decreases while land endowment is fixed. As a result, average farm size increases 23-fold. This increase in farm size over time increases the practicality of paying the fixed cost for adopting the modern technology. Third, the productivity of modern technology also improves faster than that of the traditional technology.

My calibration also provides insight into sectoral labor productivity growth of the U.S. economy. Over the twentieth century, labor productivity grows faster in agriculture than in non-agriculture. Recall that the latter only increased 6.9-fold while the former increased 30.4-fold. A portion of this difference in sectoral productivity growth can be accounted for by technology adoption. In fact, this technology adoption channel, together with its resulting capital deepening in agriculture, accounts for 3.3-fold of agricultural labor productivity growth over the twentieth century (i.e., 79.9% of the difference in sectoral productivity growth).[21]

5 Quantitative Analysis

I use the calibrated model to study cross-country differences in agricultural capital intensity and labor productivity. I focus on the comparison between the United States, which I set as my benchmark, and 20% of the poorest countries in my sample.[22]

[21]Sectoral productivity growth differs by 30.4/6.9=4.4 fold, while technology adoption contributes 3.3 fold. Therefore, this channel accounts for log(3.3)/log(4.4)=79.9% of the observed difference in sectoral productivity growth. The remaining portion is explained by the growth of κ.

[22]Recall that the 20% poorest countries in my sample, sorted by their real GDP per capita, are El Salvador, Malawi, Tanzania, Madagascar, India, Kenya, Egypt, and Pakistan.

5.1 Aggregate Factors

This experiment seeks to answer how differences in measured aggregate factors across countries can explain differences in their agricultural capital intensity and labor productivity. After discussing all results, I also use this experiment to illustrate how the technology adoption channel works in my model.

I compare the United States with the poorest 20% of countries in my sample. Note that cross-country comparable data are only available for years 1980 – 1990. For my cross-country comparison, I take the mean of the 11 years of available data for each country. The first aggregate factor I consider is land endowment (L): land endowment per capita differs by 2.13-fold between the U.S. and the poor countries. I also consider barrier to investment (η): literature has documented that poor countries have higher barriers to investment, leading to distorted prices for capital and lower capital-output ratios (Jones, 1994; Restuccia and Urrutia, 2001). The capital-output ratio, measured in the international price, is 2.08-fold higher in the United States compared to the poorest countries in the *non-agricultural sector*, so I set the barrier $\eta = 2.08$ for the poor countries.[23] The third aggregate factor I consider is the economy-wide TFP (A). Labor productivity in the *non-agricultural sector* is 4.42-fold higher in the United States versus the poorest countries. I therefore set A_{US} and A_{poor} to differ by 2.08-fold so that the differences in A and η jointly contribute to the 4.42-fold difference in non-

[23]Note that the investment-specific technology ($\{v_t\}$) and the barrier to investment (η) are not separately identified in the cross-country analysis. As a result, it is without loss of generality to assume $\{v_t\}$ to be the same across countries while η varies to match the differences in observed price of capital.

Table 3: Effects of Aggregate Factors

	Data	Model	Explained
Agriculture:			
Capital-output ratio	3.2	2.4	75%
Capital-labor ratio	165.0	27.7	65%
Labor productivity	48.8	11.4	63%
Non-agriculture (targeted):			
Capital-output ratio	2.1	2.1	-
Labor productivity	4.4	4.4	-
Whole Economy:			
GDP per capita	21.4	5.1	53%

Note:

[1] All moments are reported as the ratio between the U.S. (the benchmark economy) and the poorest 20% countries in my sample.

[2] The model's prediction is when the economy-wide TFP, barrier to investment, and land endowment are set to the level of the poorest countries.

[3] Explained portion is the ratio of log model moment over log data moment.

agricultural labor productivity. Note that I treat all differences in the non-agricultural sector as exogenous and use them to determine the aggregate factor differences. I do not target the agricultural capital-output ratio or labor productivity.

Since my cross-country data are from 1980 – 1990, I perform this experiment based on the parameter values of the year 1985. I vary the parameters $\{L, A, \eta\}$ by 2.13, 2.11, and 2.08-fold respectively as described above, and assume that the economy is in steady state. Using differences in each nations' aggregate factors only, my model can explain a sizable portion of the observed disparity in these nations' agricultural capital intensity and labor productivity. I summarize the results in Table 3. The agricultural capital-output ratio differs by 3.2-fold between the U.S. and the poorest countries, 2.4-fold of which can be explained by the model using differences in aggregate factors. Hence, the aggregate factors explain $\log(2.4)/\log(3.2) = 75\%$ of the observed differences of capital-output ratio in the data. The model also explains 27.7-fold of capital-labor ratio differences and 11.4-fold of agricultural labor productivity differences, which account for 65% and 63% of the observed differences in the data. Therefore, using aggregate factor differences only, the model can explain about two-third of the differences in agricultural capital intensity and labor productivity across countries.

The model also has implications for other moments. With differences in aggregate factors, the agricultural employment share increases to 21.3%, which is considerably higher than the benchmark U.S. economy of this period. Due to smaller land endowement and higher agricultural employment share, the average farm size of poor countries predicted by the model is around 30-fold smaller than that of the U.S., consistent with Adamopoulos and Restuccia (2014) who find that the average farm size is much smaller in poor countries. The model also predicts a much lower technology adoption rate, decreasing from nearly 100% in the U.S. to just 26.6%. This is consistent qualitatively with the evidence from the CHAT data set. According to the CHAT dataset, the poor countries in my experiment have on average 1.40 tractors per 1000 hectares, compared to 10.96 tractors per hectare in the U.S., a difference of around 8-fold.[24] Similarly, agricultural harvesters per 1000 hectares also differ by around 14-fold between the U.S. and the poor countries. Therefore, it is likely that the technology adoption rate of poor

[24] I calculate a tractor-to-land ratio instead of a tractor-to-farmer ratio. This is because farmers with tractors usually operate larger farms, so the tractor-to-farmer ratio would understate the technology adoption rate in its early stages. For example, there is more than a 360-fold difference in the tractor-to-farmer ratio between the U.S. and poor countries, which is considerably larger than if we use the tractor-to-land ratio.

countries is only 1/8 to 1/14 of that of the U.S., which is around 10%. In contrast, recall that using aggregate factor differences, the model predicts the technology adoption rate to be 26.6% in poor countries. Hence, aggregate factors alone can account for a large portion of the cross-country differences in technology adoption.

If we compare the relative importance of the aggregate factors $\{L, \eta, A\}$, the economy-wide TFP (A) is the most important factor among these three. Differences in this factor alone can generate 4.9-fold of labor productivity differences in agriculture, roughly $\frac{\log 4.9}{\log 11.4} = 65\%$ of the 11.4-fold differences when all three factors are considered. The barrier to investment η alone can generate 24% of the 11.4-fold differences, while the land endowment differences only generates 7%. This is consistent with Adamopoulos and Restuccia (2014), who also find differences in land endowment to be relatively unimportant. The remaining is contributed by interactions among these three factors.

5.2 The Channel of Technology Adoption

The novelty of my model, compared to the existing literature on agricultural productivity, is the technology adoption channel. In this section, I use the previous experiment to illustrate how this channel of technology adoption works, and why it amplifies agricultural productivity differences across countries.

Recall the previous experiment quantifying the explanatory power of aggregate factors for international differences in agricultural capital intensity and labor productivity. I now perform this experiment again without technology adoption channel: the only available technology is the modern technology. I choose to keep modern technology

Table 4: Importance of Technology Adoption

	Data	Model	No adoption
Agriculture:			
Capital-output ratio	3.2	2.4	0.9
Capital-labor ratio	165.0	27.7	6.8
labor productivity	48.8	11.4	7.3
Whole Economy:			
GDP per capita	21.4	5.1	4.8

Note:

[1] All moments are reported as the ratio between the U.S. (the benchmark economy) and the poorest 20% countries in my sample.

[2] The model's prediction is when the economy-wide TFP, barrier to investment, and land endowment are set to the level of the poorest countries.

[3] Explained portion is the ratio of log model moment over log data moment.

instead of the traditional one to make results comparable to the literature: papers in this literature often calibrate agricultural technology to the current U.S. data, resulting in an agricultural technology similar to the modern technology in my model. Table 4 compares the predictions of my model with and without technology adoption. When we shut down the channel of technology adoption, the model predicts that poor countries will have higher agricultural capital-output ratio than the U.S. (the ratio between U.S. and poor countries is 0.9), which is opposite in direction compared to data. Intuitively, poor countries have lower agricultural productivity, with inelastic demand of the agricultural good near the subsistence level of consumption. Hence, the price of the agricultural good is much higher in poor countries, and as a result, farmers can afford to use more capital in production. That is why the *real* capital-output ratio is higher in poor countries than in the U.S., although the *nominal* capital-output ratio, which equals α_m/r without technology adoption, is constant across countries in this scenario. Therefore, technology adoption is the key channel for matching the stylized fact that the cross-country differences in capital intensity are larger in agriculture than in the non-agricultural sector.

Without the technology adoption channel, the model's predictions would also suffer in other moments. For example, the predicted agricultural labor productivity differences reduce from 11.4-fold to 7.3-fold. This implies that a model without technology adoption would substantially understate the explanatory power of aggregate factors. In other words, the technology adoption channel amplifies the importance of aggregate factors in explaining the international differences in agricultural labor productivity by 1.56-fold.

The channel of technology adoption amplifies agricultural productivity differences in two ways. First, different levels of technology adoption imply different levels of agricultural capital intensity, and in turn, different labor productivity. Second and more important, technology adoption directly affects the sectoral TFP of agriculture, since modern technology is more productive and improves faster than traditional technology (B_t increases over time). To see this, consider the following equation

$$\frac{Y_a}{N_a} = \mathrm{TFP}_a^{\frac{1}{1-\alpha-\gamma}} \left(\frac{K_a}{Y_a}\right)^{\frac{\alpha}{1-\alpha-\gamma}} \left(\frac{L}{Y_a}\right)^{\frac{\gamma}{1-\alpha-\gamma}}, \tag{3}$$

which decomposes agricultural labor productivity into contributions from *endogenous* sectoral productivity (TFP_a), capital-output ratio ($\frac{K_a}{Y_a}$), and land-output ratio ($\frac{L_a}{Y_a}$). We can again look at the comparison of the model's predictions with and without technology adoption in Table 4. The model's prediction differs by 1.56-fold on labor productivity ($\frac{Y_a}{N_a}$), 1.23-fold on capital-output ratio raised by the capital share ($(\frac{K_a}{Y_a})^{\frac{\alpha}{1-\alpha-\gamma}}$), and virtually none in land-output ratio. Therefore, changes in endogenous sectoral TFP contributes to the remaining 1.27-fold difference (1.56/1.23=1.27). Note that changes in sectoral TFP are completely from technology adoption choice, since the exogenous productivity parameters A and κ are the same in this comparison. To summarize our findings from this exercise, technology adoption amplifies labor productivity differences by 1.56 folds given the aggregate factor differences, where 46.4% (=log(1.23)/log(1.56)) is from capital deepening, and the remaining 53.6% is from changes in sectoral TFP.

It is important to emphasize that so far the quantitative analysis is based on a neoclassical framework with few frictions: I assume the U.S. and the poorest countries only differ in the measured aggregate factor differences. This means that, differences in technology adoption across countries can largely explained by the price effect: it is not profitable for farmers in poor countries to adopt the modern technology and use capital to substitute labor, because the price of labor is cheap enough while modern technology is labor-saving. This result is consistent with experiences on tractor promotion projects in many Sub-Saharan countries. Between 1970–1980, various organizations provided tractors to farmers through subsidized credit or state sponsored rentals. However, most of these projects failed as "in many tractor project areas no tractors can be found today (Pingali, 2007)", mostly because human labor is cheap enough in these areas so the demand of machinery is low (Pingali et al., 1987). This evidence indicates that capital frictions, in particular the collateral constraint of acquiring machinery, are not likely to play a large role. Therefore, instead of capital frictions, I examine the role of land misallocation, which is shown as important by recent literature, to see whether they are able to account for the unexplained differences by aggregate factors.

5.3 Land Misallocation

This experiment examines the role of land misallocation. Recent literature shows that resource misallocation negatively affects aggregate productivity. In particular, land misallocation is identified as one of the main obstacles in agricultural development, since it is prevalent in low-income countries where land property rights are usually poorly defined. For example, Adamopoulos and Restuccia (2014) show that the distribution of farm size differs substantially across countries, largely due to policies and institutions that misallocate land across farmers. They further show that these differences in farm size distributions have important implications on cross-country agricultural productivity differences. Chen (forthcoming) focuses on untitled land as a specific form of land misallocation. In many poor countries, farmers do not have legal ownership of land. Local leaders grant this untitled land to farmers, usually on an egalitarian or nepotistic basis. Given that farmers are unable to trade or rent their allocated land amongst each other, the resulting operational scales of farms are generally uncorrelated with farmer ability (Goldstein and Udry, 2008; Restuccia and Santaeulàlia-Llopis, 2017). In this section, I use my model to study how untitled land can affect agricultural capital intensity and agricultural productivity.

I model untitled land following Chen (forthcoming) together with the aforementioned aggregate factors. In particular, I assume every farmer is allocated an endowment of land that cannot be traded or rented. I choose the distribution of untitled land across farmers to match the land distribution in the Malawi data described by Restuccia and Santaeulàlia-Llopis (2017), since Malawi is a country where virtually all land is untitled. In particular, they find that (log) untitled land holdings and (log) farmer ability have a weak linear positive correlation. Therefore, I assume the following functional form of untitled land across farmers:

$$\log \bar{l}_i = \beta_0 + \beta_1 \log s_i + \varepsilon_i,$$

where $\bar{l}_i$ denotes the untitled land holdings of farmer i, and ε_i is a random variable following a normal distribution with a standard deviation of σ_ε. There is no land market and the farm size distribution is exogenous among farmers. β_1 and σ_ε jointly determine the dispersion of untitled land and its correlation with farming ability. I choose $\beta_1 = 0.07$ and $\sigma_\varepsilon = 2.65$ to match two moments from Restuccia and Santaeulàlia-Llopis (2017): a dispersion of (log) untitled land holdings among farmers of 0.77, and a correlation between farmer ability and untitled land holdings of 0.12. β_0 is a scale parameter to be determined in equilibrium.

Table 5 shows the results of the enriched model with untitled land. We can see that the predictions of the enriched model match the data better. For example, the model is now able to generate a 4.1-fold difference in capital-output ratio and a 71.0-fold difference in capital-labor ratio between the U.S. and the poorest countries, which are much closer to the data. Untitled land further lowers the agricultural productivity

Table 5: Importance of Untitled Land

	Data	Model		Explained
		AF Only	w/ Unt. Land	
Agriculture:				
Capital-output ratio	3.2	2.4	4.1	121%
Capital-labor ratio	165.0	27.7	71.0	83%
labor productivity	48.8	11.4	17.5	74%

Notes:
[1] All moments are reported as the ratio between the U.S. (the benchmark economy) and the poorest 20% countries in my sample.
[2] The "AF Only" column shows the model's prediction when only aggregate factors are considered, while the next column shows the prediction after adding untitled land to the model.
[3] Explained portion is the ratio of log model moment over log data moment.

by around 54%: the model with untitled land predicts a 17.5-fold difference in labor productivity, compared to the original 11.4-fold prediction without untitled land.

Untitled land affects agricultural productivity in two ways. First, as untitled land cannot be traded/rented across farmers, there is land misallocation across farmers, which directly lowers agricultural productivity. Second, untitled land impedes technology adoption. The adoption rate of the modern technology decreases to less than 1%, compared to 26.6% without untitled land. Intuitively, modern technology is profitable only when the farm size is large enough to afford the fixed cost of technology adoption. With untitled land, however, the egalitarian allocation of land prevents higher-ability farmers from renting or buying land and operating larger farms. As a result, farmers have less incentive to pay the fixed cost of adopting modern technology.[25] Untitled land is typically thought of as a friction in the land market. However, it affects capital

[25] In reality, machinery, such as tractors, can be shared by more than one farm. My model accounts for the sharing of machinery operation costs through the setup of farmers renting capital from the market. The estimated fixed cost of technology adoption represents other costs which may not be shared between farms, such as up-front learning costs or required infrastructure for machine operation.

intensity indirectly through its impact on technology adoption. Therefore, untitled land creates joint misallocation in land and capital markets in this framework.

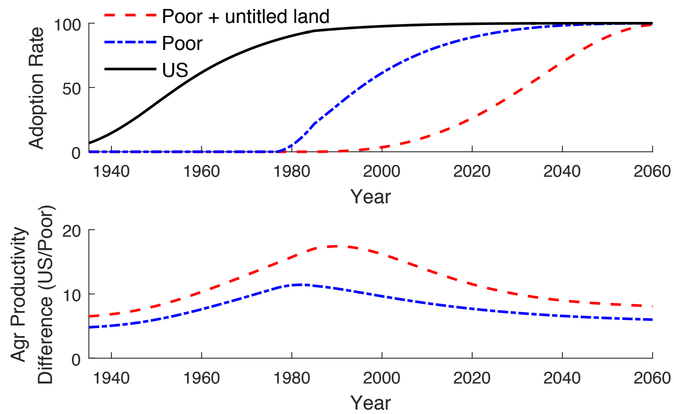
Note that other forms of land market frictions can affect technology adoption in a similar fashion. For example, imposing ceilings on farm size is another common form of land market friction. Adamopoulos and Restuccia (2015) describe a land reform in the Philippines, imposing a ceiling on farm size (5 hectares) and restricting farm land transaction. Similar to untitled land, land ceilings also prevent higher-ability farmers from operating larger farms and therefore impede technology adoption. The key similarity of these land frictions is that they prevent farms from expanding, while technology adoption depends crucially on the profitability of modern technology on large farms.

5.4 Long-Run Growth

Previous experiments study cross-country differences and show that aggregate factors and untitled land impede technology adoption in poor countries and therefore affect their current agricultural productivity. This section studies the pattern of long-run growth and convergence. In particular, I consider the following experiment: suppose we assume that productivity and endowments grow at the same rates as observed in the twentieth century. When will technology adoption happen in poor countries with untitled land? How will agricultural productivity evolve over time in poor countries relative to the U.S.?

I assume that for the period 2000–2060, time series parameters, including economy-

Figure 8: Long-Run Growth and Convergence



Note:
[1] The black solid curve represents moments in the U.S., while the red and blue dashed curves represent moments in poor countries with and without untitled land, respectively.
[2] The top panel shows the rate of modern technology adoption, defined as the percentage of output produced by farms with modern technology. The bottom panel shows differences in agricultural labor productivity between the U.S. and the poor countries, measured as $\frac{Y_a/N_a|_{\text{US}}}{Y_a/N_a|_{\text{Poor}}}$.

wide TFP (A_t), agricultural-specific productivity (κ_t), investment-specific productivity (υ_t), and population (N_t), grow at the same rates as observed for the period 1900–2000 in the U.S. These growth rates are the same for both the U.S. and the poor countries. Furthermore, I assume that aggregate factor differences between the U.S. and poor countries remain time-invariant at the same levels as in Section 5.1: $L_{\text{US},t} = 2.13L_{\text{Poor},t}$, $A_{\text{US},t} = 2.11A_{\text{Poor},t}$, and $\eta_{\text{Poor},t} = 2.08\eta_{\text{US},t}$ for all t. Untitled land is also distributed among farmers in the same way as in Section 5.3. I also assume that f_t and B_t are time-invariant after 1985. This assumption is due to the fact that technology adoption is largely completed in the U.S. and other rich countries at 1985. Therefore, it would not be profitable for research and development firms in rich countries to further improve the modern technology.

I then let the economies of both the U.S. and poor countries grow for 60 years. Figure 8 shows the long-run growth pattern of both the U.S. and poor countries, with and without untitled land. Let us first focus on the comparison between the U.S. (black solid curve) and poor countries with untitled land (red dashed line). The top panel shows that poor countries with untitled land start technology adoption roughly 75 years later than the U.S. This adoption lag translates to lower agricultural labor productivity, shown in the bottom panel. Before modern technology was adopted in the U.S., the US-poor agricultural productivity differences were predicted to be smaller than current differences. When technology adoption commenced in the U.S., US-poor agricultural productivity differences also increased. These differences peak when technology adoption is completed in the U.S. but barely initiated in poor countries. As poor countries adopt more modern technology, the differences gradually diminish. Therefore, there is a period, with length equal to the poor countries' technology adoption lag, in which US-poor agricultural productivity differences are temporarily larger due to differences in technology adoption. Note that agricultural productivity in poor countries will never be the same to that of the U.S., as illustrated in the bottom panel, due to aggregate factor differences and the existence of untitled land.

Land titling also has long-run impacts. If there were no untitled land in poor countries (i.e. farmers could sell or rent their land frictionlessly), then the technology adoption lag would be substantially shortened to around 50 years. The slope of the adoption curve would also be steeper, meaning that the adoption process would be faster. Furthermore, the agricultural productivity differences at the peak would also reduce. Comparing poor countries with untitled land (red dashed curve) to hypothetical poor countries without untitled land (blue dashed curve) in the bottom panel, we can see that untitled land has two impacts. First, it introduces static land misallocation, reflected by the distance between the two curves before technology adoption starts and after it finishes. Second, the existence of untitled land impedes technology adoption, reflected by the much wider gap between the two curves around the year 2000.

6 Conclusion

The differences of capital intensity between rich and poor countries are larger in agriculture than in non-agriculture. Meanwhile, the capital intensity of the U.S. agricultural sector increases in the 20th century. I study these phenomena using a model featuring technology adoption in agriculture, which can account for the increasing agricultural capital intensity in the U.S. Then, I use this model to perform cross-country analysis and find that countries' aggregate factors can explain around two thirds of rich-poor differences in capital intensity and labor productivity, and show that accounting for technology adoption choice is crucial for the model to match the data. I further show that untitled land, which is prevalent in poor countries, also impedes technology adoption and reduce labor productivity in agriculture.

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Appendix (For Online Publication)

A Characterization of the Model

A.1 Definition of the Competitive Equilibrium

I focus on the competitive equilibrium of this economy, which is defined as follows.

Definition 1. *Given K_0, the competitive equilibrium consists of sequences of consumption $\{c_{at}, c_{nt}\}_{t=0}^{\infty}$, investments $\{x_t\}_{t=0}^{\infty}$, farm inputs, outputs, and profits $\{k_t(s)$, $l_t(s), y_t(s), \pi_t(s)\ \forall s \in S\}_{t=0}^{\infty}$, prices of the agricultural and capital goods $\{p_t, p_t^k\}_{t=0}^{\infty}$, wages $\{w_t\}_{t=0}^{\infty}$, interest rates $\{r_t\}_{t=0}^{\infty}$, non-agricultural inputs and outputs of the representative firm $\{\tilde{K}_{nt}, \tilde{N}_{nt}, Y_{nt}\}_{t=0}^{\infty}$, aggregate capital stocks in the economy $\{K_t\}_{t=0}^{\infty}$, and measures of agricultural employment $\{N_{at}\}_{t=0}^{\infty}$, such that*

- *Given prices, interest rates, farming profits, and wages, the representative household maximizes its utility by choosing the optimal levels of consumption, investment, and agricultural employment share $\{c_{at}, c_{nt}, x_t, k_{t+1},\ N_{at}\}_{t=0}^{\infty}$.*

- *Given prices, interest rates and wages, the representative firm in the non-agricultural sector maximizes its profit by choosing $\{\tilde{K}_{nt}, \tilde{N}_{nt}\}_{t=0}^{\infty}$.*

- *Given prices and interest rates, farmers maximize farming profit by choosing the optimal level of inputs and outputs $\{k_t(s), l_t(s), y_t(s), \forall s \in S\}_{t=0}^{\infty}$.*

- *All markets clear:*

– *Agricultural good:*

$$c_{at}N_t = N_{at}\int_s y_t(s)F(ds), \quad \forall t.$$

– *Non-agricultural good:*

$$c_{nt}N_t + \frac{x_t}{\upsilon_t} + \frac{\int_s fD(s)F(ds)}{\upsilon_t} = \tilde{Y}_{nt}, \quad \forall t,$$

where $D(s)$ is a dummy indicating technology adoption choice and $\int_s fD(s)F(ds)$ is the aggregate expenditure on the fixed cost of technology adoption.

– *Capital market:*

$$N_{at}\int_s k_t(s)F(ds) + \tilde{K}_{nt} = K_t = k_t, \quad \forall t.$$

– *labor market:*

$$N_{at}\int_s F(ds) + \tilde{N}_{nt} = N_t, \quad \forall t.$$

– *Land market:*

$$N_{at}\int_s l_t(s)F(ds) = L, \quad \forall t.$$

A.2 Characterization

In each period, let c_t denote the household's per capita consumption. It can be shown that the consumption of each good satisfies

$$c_{at} = \phi\frac{c_t - p_t\bar{a}}{p_t} + \bar{a} \quad \text{and} \quad c_{nt} = (1-\phi)(c_t - p_t\bar{a}) \tag{4}$$

and the indirect utility function is given by

$$\tilde{u}(c_t, p_t) = \log(c_t - p_t\bar{a}) - \phi \log p_t + \log(\phi^\phi(1-\phi)^{1-\phi}). \tag{5}$$

The household also chooses N_{at} to maximize its labor income $N_{at}\int_{s\in S}\pi_t(s)F(ds) + (N_t - N_{at})(1-\xi)w_t$. The first order condition implies

$$(1-\xi)w_t = \int_{s\in S}\pi_t(s)F(ds). \tag{6}$$

Therefore, the total labor income of the household can be written as

$$(N_t - N_{at})(1-\xi)w_t + N_{at}\int_{s\in S}\pi_t(s)F(ds) = N_t(1-\xi)w_t. \tag{7}$$

With Equation (5) and (7), we can rewrite the household's problem as

$$\max_{c_t, x_t}\sum_{t=0}^{\infty}\beta^t N_t\tilde{u}(c_t, p_t),$$

$$s.t. \quad N_t c_t + p_t^k x_t = (1-\xi)w_t N_t + p_t^k r_t k_t + q_t L,$$

$$k_{t+1} = (1-\delta)k_t + \frac{x_t}{\eta}.$$

This problem is similar to that of a standard one-sector neoclassical growth model with the familiar Euler equation written as

$$\tilde{u}_c(c_t, p_t) = \beta\tilde{u}_c(c_{t+1}, p_{t+1})\big(\frac{r_{t+1}}{\eta} + 1 - \delta\big)\frac{p_{t+1}^k}{p_t^k}. \tag{8}$$

This equation implies a period $t+1$ interest rate of

$$\begin{aligned} r_{t+1} &= \eta\Big[\frac{\tilde{u}_c(c_t, p_t)}{\tilde{u}_c(c_{t+1}, p_{t+1})}\frac{p_t^k}{p_{t+1}^k}\frac{1}{\beta} - (1-\delta)\Big] \\ &= \eta\Big[\frac{c_{t+1} - p_{t+1}\bar{a}}{c_t - p_t\bar{a}}\frac{\upsilon_{t+1}}{\upsilon_t}\frac{1}{\beta} - (1-\delta)\Big] = \eta\Big[\frac{g_t^c g_t^\upsilon}{\beta} - (1-\delta)\Big], \end{aligned} \tag{9}$$

where g_t^c and g_t^v denote the growth rates of excess consumption (total consumption less subsistence requirements) and the investment-specific technology υ_t, respectively.

B Data

In this section, I briefly describe my data source.

B.1 Cross-country Data

I compare the following moments across countries: capital-output ratio, capital-labor ratio, and labor productivity, for both agriculture and non-agriculture. For the capital-output ratio, I study both nominal and real measures. Here, *nominal* means that capital and output are measured using *local* price, while *real* means that the moments are computed using *common* price (international dollar).

B.1.1 Benchmark Data

Capital Stock.—The data on capital stock across countries are from Larson et al. (2000). They construct measures of fixed capital stocks for both the agricultural and non-agricultural sectors.[26] Capital is measured in local price at the 1990 constant U.S. dollar, adjusted by the price deflator of each sector. Therefore, they provide *nominal* measures of capital in both sectors. I transform these nominal measures into *real* measures using the relative price index of capital provided by the Penn World Table 8.0. I assume that capital in each of the two sectors have the same price for a given

[26]FAO's database also provides measures of capital stock in agriculture, but there is no corresponding measure in the non-agricultural sector, so it is not comparable between sectors.

country.

The agricultural capital measure of Larson et al. (2000) has three components: agricultural fixed capital, livestock, and treestock, while only fixed capital is measured for the non-agricultural sector. In my analysis, I only include fixed capital as my measure of capital in the agricultural sector for three reasons. First, since only fixed capital is included in the capital measure of the non-agricultural sector, it would be more comparable to only look at fixed capital in agriculture as well. Second, as defined in the model, capital must be produced in the non-agricultural sector, which means capital goods cannot be agricultural in origin. Since livestock and treestock are agricultural in origin, it is therefore consistent with the model to exclude them. Third, not all livestock are used in production. For example, a horse is used for production while a pig is not, but both are included in the measure of livestock. Conceptually, a pig should be treated as farm output, rather than capital input. Chen et al. (2017) study household survey data in Ethiopia, and find that only a small portion of livestock are for agricultural purposes. Therefore, a cleaner measure of capital in agriculture would be only including the fixed capital stock. However, note that all of the results still hold qualitatively if I include livestocks and treestocks.

Output.—Data on nominal output (value added) at the sectoral level are available from the World Development Indicator (WDI) database, and is denominated in current U.S. dollars. The WDI also provides real output at the aggregate level, but not at the sectoral level. I therefore estimate real output for the sectoral level following Caselli

(2005) and Gottlieb and Grobovšek (2016). See the latter for details.

Employment.—Sectoral employment data are not directly available from the WDI, either. I estimate them in two steps. First, I estimate the employment share in agriculture from FAO data. FAO provides the number of economically active people in agriculture as well as in the whole economy. The ratio of the two gives the percentage of employment in agriculture. I then take the employment numbers from Penn World Table 8.0, and use agricultural employment share to back out employment numbers for both the agricultural and the non-agricultural sectors.

B.1.2 Alternative Data

Another source of sectoral capital stock and output data is the *World Input-Output Database* (WIOD) at the Growth and Development Center of Groningen University (Timmer et al., 2015). This database provides comparable data on nominal capital, nominal output, and employment for each sector. Therefore, I also use WIOD to calculate nominal capital-output ratio. Since WIOD provides a balanced panel, I perform cross-country analysis by regressing the nominal capital-output ratio on log GDP per capita, controlling for country and time fixed effects. I find that log GDP per capita is positively correlated with agricultural capital-output ratio, and is significant even after controlling for country and time fixed effects, while its correlation with the non-agricultural capital-output ratio is less significant, or even negative. I do not use these results as my benchmark, however, because the WIOD mostly only covers rich and middle-income countries, with little coverage on poor countries.

B.2 Historical Data of the U.S.

I first document historical facts of the U.S. economy over time. The agricultural sector in my model refers to the farm sector in the data. I exclude fishery, forestry, and agricultural service sub-sectors of agriculture in my analysis, as the data of these sectors are usually not available for the earlier periods.

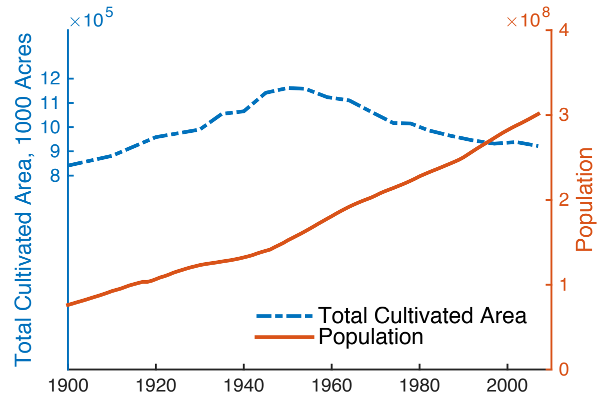
B.2.1 Aggregate Endowments

I obtain the total size of cultivated land from the *Historical Statistics of the U.S., Millennial Edition* (HSUSME), Series Da159. This series provides data on the total size of cultivated land from the years 1900 to 1997. Then I use the *U.S. Census of Agriculture (USCA)* to obtain data on the same statistic for more recent years. The data for land endowment is collected every 10 years, with higher frequencies in more recent years. Figure 9 shows the trend of total cultivated land across time. Data on the U.S. population over the past century is also obtained from the HSUSME (Series Aa125). This series provides U.S. population data up to the year 1999. Population data for more recent years come from the government census. The population trend over the past century is shown in Figure 9, with a roughly constant growth rate of 1.3%.

B.2.2 Agricultural Employment Share

I construct the statistic of the agricultural employment share by combining different sources.

Figure 9: Land and Labor Endowments



After 1948.—Agricultural employment can be grouped into three main components: wage employment, self-employment, and unpaid family labor. The Bureau of Economic Analysis (BEA) estimates hours of wage employment across sectors from 1948 to 1999 (Table 6.9), as well as the number of full-time and part-time employees at the sectoral level (Table 6.4). The BEA also estimates the number of self-employed persons at the sectoral level (Table 6.7). Unpaid family labor data are taken from the HSUSME (Series Ba930-932). However, the labor hours of these two latter categories are unavailable. Therefore, I assume the average hours of self-employed persons and unpaid family labor to be the same as those of wage employees, following Herrendorf et al. (2015). I use this to obtain aggregate labor hours of the farm and non-farm sectors for the years after 1948. Note that, since the HSUSME ends in the year 1999, I extrapolate my data to the year 2000 by assuming that the agricultural employment in 2000 is the same as that of 1999.

1900 - 1948.—I use the estimated labor hours reported in Kendrick (1961) between the years 1900 and 1948. Table A-X of Kendrick (1961) provides the aggregate labor hours for the farm and non-farm sectors of the U.S., which include wage employment, self-employment, and unpaid family labor. For the year 1948, Kendrick's estimation overlaps with that of the BEA. In this year, Kendrick's estimate for the agricultural employment share is slightly lower than that of the BEA. I therefore scale up Kendrick's estimation over the period 1900 – 1948 to make it comparable with that of the BEA. Figure 7 shows the agricultural employment share of the U.S. over time.

Note that Lebergott (1984) also estimates the agricultural employment share for pre-1960 U.S. Lebergott's estimates are generally higher than the data I am using; for example, in 1900, the agricultural employment share is around 33% in my data, while Lebergott (1984) estimates it to be around 40%. This discrepancy is likely due to the fact that Lebergott's estimation does not account for differences in labor hours between sectors: Kendrick (1961) points out that the average hours of farmers are substantially lower than that of non-agricultural workers before the 1940s, while they are similar thereafter.

B.2.3 Capital Stock and Output Over Time

I use two measures of capital stock and output: a (nominal) current price measure and (real) chain-type quantity indices.

Nominal Capital and Output.—The nominal measure (current cost) of capital is from Table 6.1 and Table 7.1 of *National Income and Product Accounts* (NIPA). Table 6.1 provides the nominal capital stock of the farming, manufacturing , and non-farm non-manufacturing sectors; Table 7.1 provides the nominal capital stock owned by the government. The capital stock of farms corresponds to the nominal measure of capital stock in agriculture in my paper, while the remaining components sum up to that of the non-agricultural sector.

I collect data on the nominal output (value added) of agriculture and the whole economy from the NIPA tables. Table 7.3.5 reports the nominal value added of the farming sector. Note that the BEA does not include "rent paid to non-operator landlords" in its value added statistic of agriculture. However, Herrendorf et al. (2015) argue that this component should be counted in the value added of agriculture, so I add this component to the value added of agriculture. Table 1.1.5 provides the measure of nominal GDP for the whole country. I subtract agricultural value added from this to obtain non-agricultural value added.

Chain-Type Quantity Indices of Capital.—The BEA also reports a (real) chain-type quantity index of capital. Note that this chain-type quantity index is not additive (Whelan, 2002). NIPA Table 4.2 provides the quantity indices of farm capital and other non-farm private capital; Table 7.2 provides the quantity index of government capital. The real measure of capital in my paper refers to these quantity indices.

Real Measure of Output.—The real measure of output is the chain-type quantity index of output from the BEA. NIPA Table 7.3.3 has the quantity index of the value added of the farming sector, and I also adjust it to include the rent paid to non-operator landlords. Table 1.5.3 has the quantity index of the GDP of the whole economy. I subtract the agricultural (farm) sector GDP from total GDP to obtain the quantity index of the non-agricultural (non-farm) sector.

These data series from the BEA are only available starting from 1929. To construct real sectoral value added for the period 1900 – 1929, I use the estimation of real value added from Table A-III of Kendrick (1961), which provides real value added of the farm sector and the total economy, using the 1929 fixed price deflator. I compute the real value added for the period 1900 – 1929 as percentages of the 1929 level and then use these to supplement the data series from the BEA.

The Relative Price of Investment.—The relative price of investment goods versus consumption goods decreases over time (Greenwood et al., 1997). NIPA Table 1.5.3 and Table 1.5.5 provide the (real) chain-type quantity indices and nominal values of the national account. The price indices are the ratio of those two. In the national account, consumption goods are aggregated from three components: consumer non-durables, services, and government consumption. Investment goods also aggregates from three components: consumer durables, private investment, and government investment. The relative price of investment goods versus consumption goods is shown in Figure 5. Note that my measure differs from Greenwood et al. (1997), since they only consider the relative price of equipment versus consumption goods, while I also include structures, consumer durables, and residential components as part of investment goods.

B.2.4 Ability Distribution

I calibrate the farmers' ability to the distribution of value added across farms using data from the *2007 U.S. Census of Agriculture* (USCA), following the method described in Adamopoulos and Restuccia (2014). The data are from Table 58 of the 2007 USCA, "Summary by Farm Size". Value added in dollars is calculated as the difference between gross output (measured as sales) and intermediate inputs. Intermediate inputs include seed, feed, fertilizer and other chemicals, gasoline and other fuels, utilities, supplies, repairs and maintenance. Note that the census categorizes farms into different bins by size, and provides the number of farms in each bin. Then I calculate the distribution of farm value added across bins. I choose the ability distribution in my model so that the distribution of farm value added in my model best matches the data. Figure 4 compares the distribution of value added in the data with that of my calibration.

One difference between my calibration and Adamopoulos and Restuccia (2014) is that I calibrate the ability distribution to match the distribution of farm value added in the data, while they calibrate it to match the farm size distribution. They use a constant elasticity of substitution technology, where ability is land augmenting, to capture the fact that the dispersion of farm size is much larger than the dispersion of value added. Since my paper does not focus on farm size distribution, I abstract from this feature and use Cobb-Douglas technologies for simplicity.

Note that in the USCA there are two ways to sort farms: Table 58 of USCA sorts farms by farm size, and Table 59 sorts farms by their sales. Both farm size and sales can be indicators of farmer ability; sales are, however, less robust to stochastic output shocks (like rainfall shocks), while farm size is a more stable indicator over time and better reflects farmers' true ability.[27] Once we sort farms into bins by size and compute the average value added for each bin, the stochastic shocks cancel out since stochastic output shocks are not correlated with farm size and there are sufficiently large numbers of farms within each bin. In contrast, if we were to sort farms according to their sales, the stochastic shocks would not cancel out, since sales are correlated with output shocks. The following example helps illustrate this problem.

Example 1. *Suppose half of farmers have high ability* $s_h = 2$ *and the other half have low ability* $s_l = 1$*. Their farm sizes are* $l_h = 1000$ *and* $l_l = 100$*. Note that farm sizes are not exactly proportional to ability as in Adamopoulos and Restuccia (2014). Their sales without shocks are* $y_h = 200$ *and* $y_l = 100$*, with intermediate input* $m_h = 50$ *and* $m_l = 25$*. Suppose half of farmers get a good output shock, i.e.,* $\varepsilon_g = 1.5$*, and the other half get a bad shock* $\varepsilon_b = 0.5$*. As a result, we observe four types of sales: high-ability, good-shock:* $y_h\varepsilon_g = 300$*; high-ability, bad-shock:* $y_h\varepsilon_b = 100$*; low-ability, good-shock:* $y_l\varepsilon_g = 150$*; low-ability, bad-shock:* $y_l\varepsilon_b = 50$*. If we sort them by farm size, the value added of the higher half over that of the lower half is*

$$\frac{\sum_i \sum_j (y_i\varepsilon_j - m_i)\mathbb{1}[l = 1000]}{\sum_i \sum_j (y_i\varepsilon_j - m_i)\mathbb{1}[l = 100]} = \frac{(y_h\varepsilon_g - m_h) + (y_h\varepsilon_b - m_h)}{(y_l\varepsilon_g - m_l) + (y_l\varepsilon_b - m_l)} = \frac{250 + 50}{125 + 25} = 2,$$

[27] Note that farm size and ability may not map into each other in a linear way, as argued in Adamopoulos and Restuccia (2014). My analysis here only assumes that the *rank* correlation between farm size and ability is higher than that between farm sales and ability.

which is a correct measure of the ability. If we sort them by their sales, we have

$$\frac{\sum_i \sum_j (y_i\varepsilon_j - m_i)\mathbb{1}[y_i\varepsilon_j \geqslant 150]}{\sum_i \sum_j (y_i\varepsilon_j - m_i)\mathbb{1}[y_i\varepsilon_j < 150]} = \frac{(y_h\varepsilon_g - m_h) + (y_l\varepsilon_g - m_l)}{(y_h\varepsilon_b - m_h) + (y_l\varepsilon_b - m_l)} = \frac{250 + 125}{50 + 25} = 5,$$

which overestimates the dispersion of ability.

B.2.5 Technology Adoption

For illustration purposes, this section describes how I construct the adoption curve for farms with tractors. I then repeat this process for other machines and take the average to obtain the technology adoption curve used in this paper.

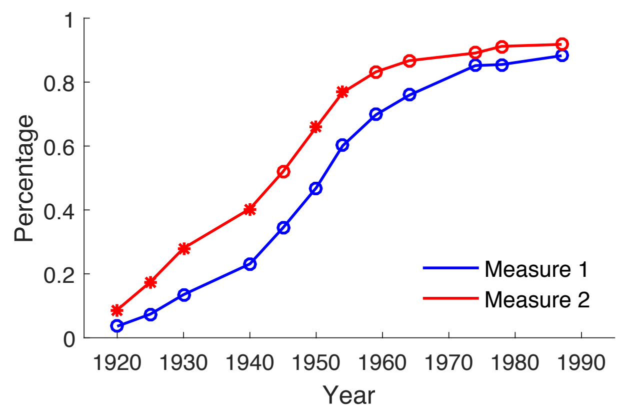
If a farm uses at least one tractor, I treat this farm as a farm with modern technology. The first measure of technology adoption (Measure 1, hereafter) is the percentage of farms with tractors defined as

$$\text{Measure 1} \equiv \frac{\sum_i \mathbb{1}_i\{\text{Tractor} \geqslant 1\}}{N},$$

where N stands for the total number of farms. I calculate the percentage of farms with tractors from the historical publications of the USCA for the years 1920, 1930, 1940, 1945, 1954, and every 5 years after this. The earliest observation is in the year 1920 in which only 3% farms had tractors. Since even fewer tractors were in use before this time, let us assume that technology adoption started in 1920. The blue line of Figure 10 shows the evolution of this measure over time.

Measure 1 is intuitive but it does not take into account the fact that farms adopting modern technology (tractors) tend to be larger than other farms. Therefore, I define

Figure 10: Technology Adoption



Note: This figure shows Measure 1 and Measure 2 of technology adoption (see definition in text) over time. Circles represent data points, while stars indicate estimated values.

an alternative as

$$\text{Measure } 2 \equiv \frac{\sum_i \mathbb{1}_i\{\text{Tractor} \geqslant 1\} y_i}{\sum_i y_i}.$$

It measures the percentage of output produced by farms with tractors. It is shown as the red line in Figure 10.[28] It is clear that Measure 2 is always larger than Measure 1, confirming my conjecture that farms with modern technology (tractors) are in general larger. I use this second measure as my measure of technology adoption in the paper since it takes into account size differences between adopters and non-adopters of modern technology.

Technically, these two measures map into each other: given the number of farms with modern technology, the model can generate the fraction of output produced by these farms with modern technology. However, the actual mapping observed in the data

[28]Note that instead of publishing data at the farm level, the USCA groups farms into different bins according to relevant features like farm size, and then publishes statistics at the bin level. As a result, I assume farms within each bin are homogeneous when I calculate my statistics.

differs from that of the model. In the model, larger farms adopt modern technology strictly earlier than smaller farms (a property of the threshold model of technology adoption). Although we do generally observe this to be true in the data, there are some small farms that also adopt the modern technology early due to unobserved heterogeneity which we abstract from in the model. As a result, if I use Measure 1 in my calibration to match the percentage of farms adopting modern technology, the model result will be inconsistent with the data in terms of the contribution of modern technology adopting farms to total output, which is important in determining agricultural productivity. This can be corrected by introducing an error term in the model to account for the unobserved heterogeneity in technology adoption, but this would unnecessarily complicate the model.

The problem with Measure 2, however, is that it can only be constructed for the years 1945, 1959, 1974, and later (red circles in Figure 10), while Measure 1 is available all the way back to 1920. For the years in which Measure 2 is not directly available, I calculate it from Measure 1 by estimating a threshold model with unobserved heterogeneity, which I will explain below. The estimated data points are labelled as red stars in Figure 10.

I then normalize the adoption rate in the final year to be 100% and scale up the whole time series proportionally to obtain the adoption curve for tractors. I repeat this process for four other types of modern machinery: trucks, combines, balers, and conditioners. I then take the average of these five curves to derive the technology adoption curve used in this paper.

A threshold model with unobserved heterogeneity.—Assume that farmers with ability s_i adopt the modern technology if $s_i > \frac{f_t}{e_{it}}$, where f_t is the fixed cost of adopting the modern technology at period t, and e_{it} is a random variable independent of ability following a lognormal distribution with standard error σ_e. We can interpret this as the unobserved heterogeneity of technology adoption. Modern technology is adopted if $\log(e_{it}) < \log(f_t) + \log(s_i)$. and therefore the percentage of technology-adopting farms is given by $\Phi(\log(f_t) + \log(s_i))$. The distribution of s_i has been estimated previously in Section B.2.4. Only f_t and σ_e remain to be estimated. We have the following two moments for each period:

$$\text{Measure 1} = \frac{\sum_i \mathbb{1}\{\log(e_{it}) < \log(f_t) + \log(s_i)\}}{N_t},$$

$$\text{Measure 2} = \frac{\sum_i \mathbb{1}\{\log(e_{it}) < \log(f_t) + \log(s_i)\} y_{it}}{\sum_i y_{it}}.$$

I pick three years (1945, 1959, 1978) where both measures are available and there exists adequate variation in both measures to estimate $\{\sigma_e, f_{1945}, f_{1969}, f_{1978}\}$. We have six moments (two in each period). The estimation algorithm is as follows. 1) Guess an initial value of σ_e. 2) Use Measure 1 in each period to estimate f_t. 3) Substitute f_t into the expression of Measure 2 and compare the estimated Measure 2 with the true Measure 2 from the data to obtain the error term for each period. 4) Define the loss function as the sum of the squared error of each period. 5) Update the guess of σ_e to minimize this loss. After determining time-invariant σ_e, I then use this model to estimate Measure 2 from Measure 1 for the years in which Measure 2 is unavailable.