Education Policy, Human Capital and Structural Transformation*

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Abstract: This study investigates the impact of public education policy on both human capital accumulation and structural transformation across time and space. A life-cycle model is developed, featuring heterogeneous agents who make decisions related to education and sectoral employment. The model accounts for both the quantity and quality dimensions of education, and performs well in both developing and developed countries. A quantitative analysis reveals that education policy alone is responsible for more than 10% decline in the U.S. agricultural employment share over the last century. Furthermore, improving education policy worldwide is essential for reducing global disparities in human capital and driving structural transformation in low-income countries.

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1 Introduction

The structural transformation process is a significant feature of economic development, occurring during sustained periods of rising income. This transformation involves a shift of economic activities from the agricultural sector to nonagricultural sectors. Two mechanisms have been identified in the literature to explain this trend: first, growth in income reduces the relative demand for food; second, technological advancements in agriculture alleviate subsistence constraints. Both mechanisms lead to decreased demand for agricultural laborers, resulting in the agricultural sector's gradual decline over time.

This article advances the idea that human capital plays a pivotal role in determining structural transformation. Human capital tends to be more valuable in the nonagricultural sector, leading individuals with larger human capital stock to prefer working in nonagricultural sectors (Herrendorf and Schoellman, 2018; Porzio, Rossi and Santangelo, 2022). Therefore, beyond income and productivity channels, an increase in human capital may significantly contribute to driving structural transformation. The left panel of Figure 1 shows that, indeed, economies with larger human capital stock tend to have smaller agricultural employment shares.[1]

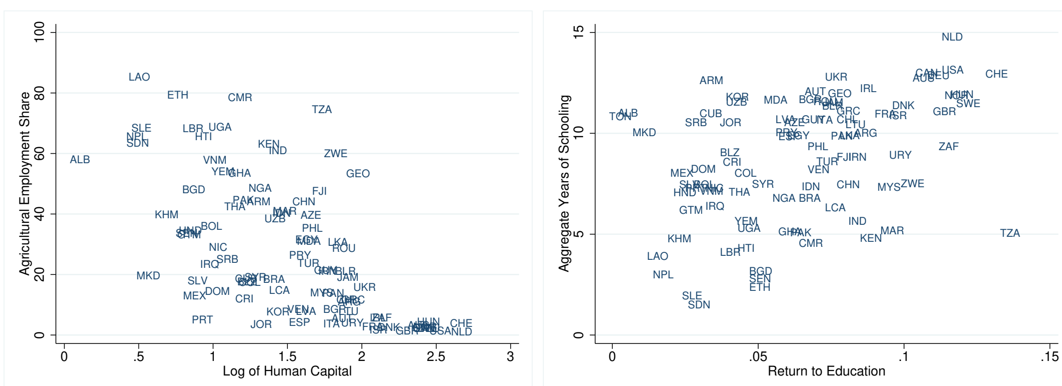

Figure 1: Sectoral Allocation, Years of Schooling and Return to Schooling.

To measure human capital, we emphasize both quantity and quality dimensions of education. Quantity of education refers to the number of years of schooling, whereas quality of education refers to the amount of human capital acquired per year of schooling, as can be

[1] The human capital stock measure (H) follows a functional form suggested by Schoellman (2012), $H = \exp[(SQ)^{0.5}/0.5]$, where years of schooling (S) is taken from Gollin, Lagakos and Waugh (2014), and the return to education (Q) is taken from Schoellman (2012). We use the method proposed in Hendricks (2002) and Schoellman (2012) and assess education quality in immigrants' original countries by examining their earnings in the U.S. Other studies estimate human capital stock directly using international testing scores (e.g., Hanushek and Kimko, 2000; Hanushek, Ruhose and Woessmann, 2017; Lee and Lee, 2022).

inferred from the Mincer return, i.e., the increased wage income for each additional year of schooling (see, e.g., Hendricks, 2002; Schoellman, 2012). The right panel of Figure 1 reveals that although there is a positive and significant relationship between years of schooling and return to education, this association is not very strong ($R^2 = 0.2$). For countries with similar schooling years, the return to education varies widely. For instance, an average worker in both the UK and Italy received about 11 years of schooling in 2005; the return to education, however, was 11% in the UK compared to 7% in Italy.[2] Hence, years of schooling and return to education are interconnected but distinct aspects of human capital investment.

In this study, we delve into the systematic variations in human capital accumulation across countries, emphasizing public education policy. We explore two dimensions of education policy: government-subsidized schooling years and public education expenditure. These facets are vital in determining a nation's human capital stock through their influence on both the quantity (years of schooling) and quality (return to schooling) of education.[3] A better education system reduces the education's marginal cost while increasing its marginal benefit, thereby fostering human capital accumulation. This, in turn, leads to increased labor productivity and a transition away from the agricultural sector.[4] Our empirical findings support the proposition that more schooling years and higher Mincer returns to education correlate with increased labor productivity, particularly in the nonagricultural sector. In addition, countries with more extensive human capital stocks tend to have smaller agricultural employment shares.

Armed with this evidence, we develop a life-cycle model that integrates human capital and sectoral employment decisions within a multi-sector general equilibrium framework. Our approach to modeling human capital accumulation builds upon the work of Córdoba and Ripoll (2013), though we diverge in two essential ways: first, by incorporating human capital accumulation into a multi-sector general equilibrium context where nonagricultural sector relies more on human capital than agricultural sector; and second, by introducing household heterogeneity in terms of wealth and abilities endowments to accommodate different education policy responses by households with different endowments. The model not only predicts sectoral employment shares but also generates endogenous sectoral productivity differences based on workers' human capital.

Human capital accumulation is influenced by both the duration of schooling and invest-

[2] In 2005, the agricultural employment share was 2% in the UK and 4% in Italy.

[3] In the data, we use compulsory years of schooling as a proxy for the duration of government-subsidized years of schooling.

[4] While it is widely accepted that education boosts productivity in nonagricultural sectors, Goldin and Katz (2010) shows that individuals with higher education earn more than others within the agricultural sector but still have a lower Mincer return than those in nonagricultural sectors.

ment in education during the schooling period. Government education policy, including the subsidies provided per pupil and their duration, affects human capital investment. Education subsidies diminish the marginal costs for individuals and augment the marginal benefits of private education investment, leading to increased human capital investment. Extending the duration of these subsidies enhances this effect. As households accumulate more human capital, they become more inclined to choose nonagricultural employment. The model thus explains why economies with superior education policies generally have higher schooling levels and a smaller agricultural sector.

For the quantitative analysis, we calibrate the model using U.S. data circa 2000, treated as our baseline economy.[5] Among the untargeted moments, the model generates within-sector distributions of schooling years that align with the data. By adjusting the parameters to reflect the U.S. economy at around 1900, our model explains over half of the decline in the agricultural employment share and nearly all of the increase in schooling years over the past century. Counterfactual analysis shows that education policy alone, including government-subsidized schooling duration and public education expenditure, accounts for more than 10% of the observed structural transformation over the past century.

To explore the cross-country variations in human capital accumulation, structural transformation, and productivity, we recalibrate the model for countries ranging from low to high percentiles in the world's income distribution.[6] Next, we test the model's ability to predict differences in agricultural employment share and human capital, both untargeted, demonstrating that our model replicates the observed cross-country patterns.[7] Moreover, we validate the model by simulating empirical experiments in developing countries, including offering secondary school scholarships (Duflo, Dupas and Kremer, 2021) and nationwide school construction (Duflo, 2001; Karachiwalla and Palloni, 2019; Porzio, Rossi and Santangelo, 2022). Our model produces changes in schooling years or declines in agricultural employment share highly consistent with empirical findings in these developing countries.

In counterfactual exercises, we find that eliminating public education policy would lead to an average 27% reduction in human capital stock and an average 13% rise in agricultural

[5]The targeted moments include sectoral employment and value-added shares, sectoral wage distribution, sectoral years of schooling and return to schooling, public and private education expenditure, and some wealth-distribution-related moments, all of which match the data well.

[6]Specifically, we recalibrate the parameters related to sectoral technology and public education policy to match output per worker, education expenditure share, and sectoral years of schooling for each country.

[7]The human capital measure is derived from the return to education of U.S. immigrants from various countries, as reported by Schoellman (2012). We do not use return to education data from a country's own census or survey, such as in Psacharopoulos (1985, 1994), since they depend on both the quality of education and the total human capital stock. In countries with lower levels of education, secondary school completion may be considered higher education, earning premium wages. Thus, controlling for human capital stock when measuring education quality is desirable, as argued in Schoellman (2012).

employment share across countries. Conversely, uniformly implementing the U.S. public education policy across all nations would increase the average human capital stock by 47% and decrease the average agricultural employment share by 8%. Interestingly, while both experiments eradicate disparities in public education policy, adopting the U.S. education policy decreases inequality in human capital and agricultural employment share, whereas zero-education-policy increases them. This outcome highlights the necessity of establishing superior public education systems globally to close the disparities in human capital stock and foster structural transformation into more productive nonagricultural sectors in low-income countries.

We also investigate the impacts of two dimensions of education policy on aggregate labor productivity, examining the effect of public education expenditure per pupil per year and subsidized years of schooling, respectively, to U.S. standards. First, we find that the impacts of both education policies diminish with a country's existing education expenditure or subsidized schooling years relative to the U.S. standard, indicating education policy's crucial role in world income convergence. Second, equalizing education expenditure has a more pronounced effect than equalizing years of subsidized schooling, suggesting its greater potential to enhance aggregate productivity.

Finally, we compare education policy to a policy that directly enhances sectoral TFP. Traditionally, policy makers usually implement industrial policies that subsidize agricultural and nonagricultural technologies, to create push and pull effects toward industrialization. We show in this paper that education policy yields better outcomes than such industrial policies. Specifically, we adjust sectoral TFP for each country in the first quintile to equate to the agricultural employment shares attained when their education policy is aligned with that of the U.S. We find that implementing the U.S. education system in these nations is tantamount to a 4% increase in agricultural TFP or an 11% increase in nonagricultural TFP. However, education policy has a more profound impact on labor productivity, boosting GDP per worker by 17% on average. This effect is 3.8 and 6.2 times greater than that in the progress in agricultural and nonagricultural TFP, respectively. These findings underscore the relative importance of education policy in enhancing labor productivity.

Related Literature. Our work expands upon the self-selection model of Roy (1951), which is based on comparative advantage. Our framework is similar to those of Lagakos and Waugh (2013) and Porzio, Rossi and Santangelo (2022). While Porzio, Rossi and Santangelo (2022) emphasizes the role of human capital growth in driving structural transformation, they do not model endogenous education investment, restricting their ability to simulate human capital responses to education policy. Our contribution centers on endogenizing human capital accumulation, connecting it to education policy and the economic environment, and quantifying its influence on structural transformation. We also take into account the quantity and quality of education. To the best of our knowledge, we are the first to gauge the effects of these dimensions on structural transformation.[8]

Our model shares similarities with those of Córdoba and Ripoll (2013) and Manuelli and Seshadri (2014). Specifically, we adopt Córdoba and Ripoll (2013)'s method for modeling human capital accumulation. Both our study and theirs examine how various education policies, income levels, and overall efficiency influence individual investment in human capital. In our exploration of structural transformation, we introduce multiple production sectors within a general equilibrium framework. This approach allows individuals with different endowments to invest in diverse levels of human capital, enabling them to self-select into various sectors. Furthermore, our research supplements the human capital literature by merging both quantity and quality aspects of education into a life-cycle model. This method allows us to account for quality-adjusted human capital stock in a way akin to Manuelli and Seshadri (2014), and use it to explore structural transformation.[9]

Caselli and Coleman (2001) is the seminal paper investigating education's effect on labor's sectoral allocation. Our study differs from theirs in our treatment of human capital. In Caselli and Coleman (2001), education serves only as a requirement for entry into the nonagricultural sector, without influencing individual productivity. Conversely, we view human capital as a productive input. As noted by Manuelli and Seshadri (2014), different human capital levels impact the economy's aggregate productivity levels. Our multi-sectoral framework allows us to use the measured sectoral human capital stock to examine both labor allocation and productivity across sectors.

Finally, our model adds to the extensive literature on structural transformation, as outlined in the review by Herrendorf, Rogerson and Valentinyi (2014). Our research aligns with Acemoglu and Guerrieri (2008), who created a model based on Rybczynski (1955). This model demonstrates how endogenous variations in input supplies can generate structural transformations if sectors have different factor intensities. Our contribution consists of constructing a model that endogenizes human capital formation and links it to structural

[8]Cheung (forthcoming) uses a two-sector model to evaluate education policies' impact on the trade-off between child-rearing quantity and quality concerning structural transformation in the U.S. Nevertheless, his research neither differentiates between the quantity and quality dimensions of education nor explores structural transformation across various countries.

[9]Using fixed Mincer coefficient to estimate human capital, as demonstrated in studies such as Bils and Klenow (2000) and Gollin, Lagakos and Waugh (2014), could result in a subdued responsiveness of the human capital stock to fluctuations in macroeconomic elements like TFP and education policies. Manuelli and Seshadri (2014) suggests that such estimates might underestimate the role human capital plays in propelling economic development.

transformation, extending the existing literature by emphasizing the role of human capital – and, by extension, education policy – in shaping structural transformation.

2 Stylized Facts

We now showcase empirical evidence that explores the negative correlation depicted in the left panel of Figure 1 above. We focus on evidence that connects education policy to education attainment across countries, taking into account both quantity (as measured by years of schooling) and quality (as measured by the return to schooling). Moreover, we illustrate that increased education attainment is associated with decreased agricultural employment and increased labor productivity, particularly within the nonagricultural sector.

Fact 1. Education Policy Correlates Positively with the Quantity and Quality Dimensions of Education

Different dimensions of education policy, including compulsory years of schooling and government public education spending, show significant variations across countries. For instance, in 2005, Bangladesh enforced a 5-year period of compulsory education, dedicating 2.1% of its GDP to education, while the United States mandated a 12-year compulsory education period, allocating 4.9% of its GDP to education.[10]

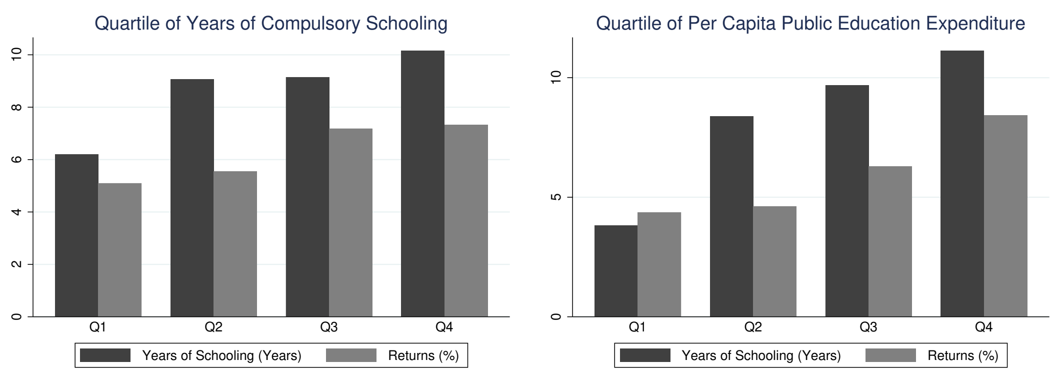

Figure 2: Quantity and Quality of Education by Education Polices Quartile.

These variations in education policy influence both quantity and quality of education, as indicated by the years of schooling and returns on education (Schoellman, 2012). Figure 2 illustrates that countries adopting more supportive education policies, characterized by

[10]In the model, we treat education policy as encompassing government-subsidized years of schooling as well as public education spending. Due to the absence of data on government-subsidized years of schooling, however, we use compulsory years of schooling as a proxy.

longer compulsory education duration and greater public expenditure in education, typically have higher years of schooling. This pattern can be attributed to better education policy lowering the incremental cost of education, resulting in an overall extension in the length of schooling. Additionally, improved education policy often leads to a higher level of human capital gained per year of schooling, increasing the Mincer return. As a result, the benefits derived from education are enhanced.

Fact 2. The Nonagricultural Sector Relies More Heavily on Human Capital and Responds More to Changes in the Quantity and Quality of Education

The nonagricultural sector's dependence on human capital is more pronounced, reacting more to changes in both the quantity and quality of education, than that of the agricultural sector. Various scholars validate this observation (see, e.g., Goldin and Katz, 2010; Herrendorf and Schoellman, 2018; Porzio, Rossi and Santangelo, 2022). Figure A.1, in the appendix, based on data from Gollin, Lagakos and Waugh (2014), illustrates that the years of schooling achieved in the nonagricultural sector consistently surpass those in the agricultural sector across all countries analyzed.

Sectoral labor productivity provides insight into the efficiency of labor within a given sector. We calculate it using the equation:

$$\frac{Y_i/Y}{N_i/N} = \frac{Y_i}{N_i} \times \frac{N}{Y} \iff \frac{Y_i}{N_i} = \frac{Y_i/Y}{N_i/N} \times \frac{Y}{N}$$

where Y_i/N_i represents sectoral labor productivity, Y/N is GDP per worker, Y_i/Y is the sectoral value-added share, and N_i/N is the sectoral employment share. Using data from World Bank (2023) and Gollin, Lagakos and Waugh (2014), we craft a metric to measure sectoral labor productivity. Our evaluation reveals a positive link between both the quantity and quality of education and an increase in sectoral labor productivity, as in Figure 3.

We then use ordinary least squares to study the effect of education's quality and quantity on sectoral productivity. This analysis illustrates a more robust association between quantity and quality of education and labor productivity in the nonagricultural sector than in the agricultural sector. Specifically, an additional year of schooling correlates with a 0.40-unit increase in agricultural productivity, while it corresponds to a 0.68-unit increase in nonagricultural productivity. Moreover, a 1 percentage point rise in the Mincer coefficient, taken from Schoellman (2012), is associated with a 0.42-unit increase in agricultural productivity and a 0.57-unit increase in nonagricultural productivity. These findings indicate that human capital is leveraged more intensely in the nonagricultural sector than in the agricultural sector. Consequently, Facts 1 and 2 imply that, although improved public education policy can

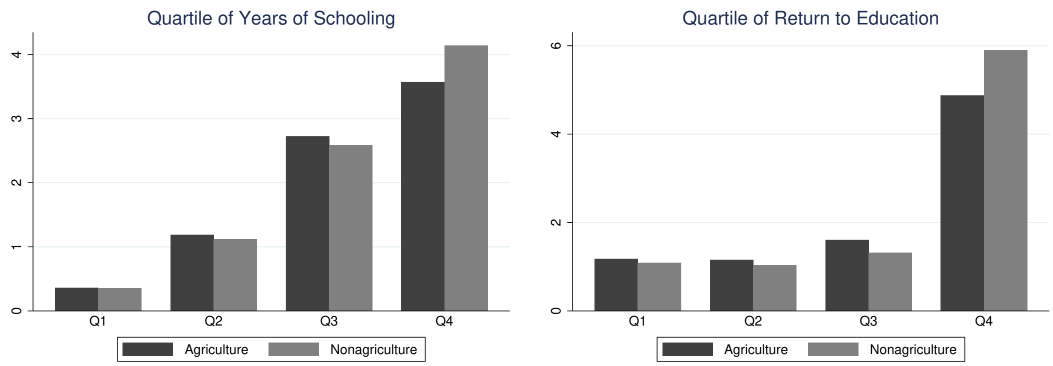

Figure 3: Sectoral Productivity Levels by Quantity and Quality of Education Quartile.

boost labor productivity in both sectors, the impact is more pronounced in the nonagricultural sector.

Fact 3. The Quantity and Quality of Education Negatively Correlate with the Agricultural Employment Share

As established in Fact 2, the quantity and quality of education are positively linked to sectoral labor productivity. This increased productivity eases subsistence food constraints, leading to a subsequent rise in income and a reduced relative demand for food. Simultaneously, individuals with more human capital have a comparative advantage in nonagricultural production, making them more inclined to work in the nonagricultural sector. These combined factors contribute to a shift in labor from agriculture to nonagriculture. Figure 4 shows that countries with higher levels of educational quantity and quality typically have lower shares of agricultural employment, and the pattern observed in the left panel of Figure 1 is influenced by both the quantity and quality of education.

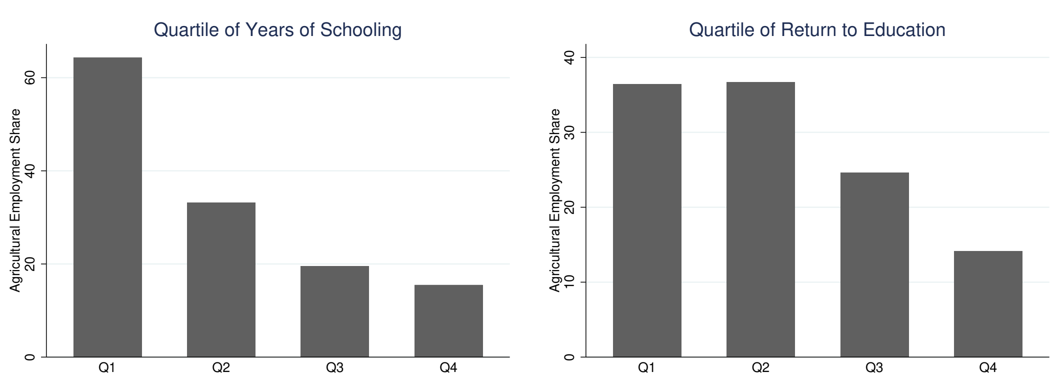

Figure 4: Agricultural Employment Share by Quantity and Quality of Education Quartile.

2.1 Taking Stock

We explore several stylized facts to unravel the mechanisms behind the negative correlations between human capital and agricultural employment. Our argument emphasizes the role of improved education policy, contributing to an increase in both the quantity and quality of education. This, in turn, fosters human capital accumulation. The resulting enhancement in human capital boosts labor productivity in all sectors, with a particularly notable effect in the nonagricultural sector. These lead to a corresponding rise in the nonagricultural sector and a decrease in the agricultural sector. There is also evidence suggesting that the mechanism is causal. Duflo (2001) demonstrates that improvements in the public education system lead to increase schooling, while Porzio, Rossi and Santangelo (2022) show that an increase in years of schooling contributes to the expansion of the nonagricultural sector.

3 Model

We now develop a life-cycle model that integrates human capital and sectoral employment decisions within a general equilibrium framework, and use this model to assess the importance of education policy on structural transformation. Our model of human capital accumulation extends the approach proposed by Córdoba and Ripoll (2013) to a multi-sector general equilibrium context, allowing for individual heterogeneities. Consequently, our model endogenizes the interaction between human capital accumulation and sectoral employment decisions, drawing on the framework of Roy (1951). Financial constraints and education policy are thus crucial elements that guide individual investments in the quantity and quality of education, and in their choices in sectoral employment.

3.1 Household and Endowment

Time is continuous.[11] Individuals differ in ability (ψ), agricultural productivity (l), and initial wealth (b),[12] which are randomly distributed according to $G(\psi, l, b)$. While agricultural productivity (l) influences individuals solely through agricultural production efficiency, ability (ψ) impacts both non-agricultural production efficiency and human capital accumulation. To concentrate on the sectoral distribution of human capital rather than intergenerational

[11]The assumption of continuous time simplifies the first-order conditions, particular the one concerning years of schooling.

[12]Heterogeneity in initial wealth b is crucial for generating different wealth effects in education decision and different responses to education policy based on wealth (Lochner and Monge-Naranjo, 2011). Heterogeneity in ψ and l are motivated by Lagakos and Waugh (2013), who assume different levels of individual productivity in agricultural and nonagricultural sectors.

mobility, we ignore intergenerational choices.

The economy has two sectors: agricultural (a) and nonagricultural (m), with $i \in \{a, m\}$. The instantaneous *indirect* utility function is given as[13]

$$u(c(\tau)) = \left[\frac{c(\tau) - p_a(\tau)\bar{c}}{[\zeta p_a(\tau)^{1-\eta} + (1-\zeta)p_m(\tau)^{1-\eta}]^{\frac{1}{1-\eta}}} \right]^{1-\sigma} /(1-\sigma) \tag{1}$$

where $c(\tau)$ is total consumption expenditure at age τ. The parameter $\bar{c} > 0$ is the subsistence level of agricultural consumption, so that agricultural goods have a lower income elasticity than nonagricultural goods. In addition, p_a and p_m are the prices of agricultural and nonagricultural goods, respectively. We set $p_m = 1$ making nonagricultural goods the numèraire, and measure education expenditures in terms of numèraire. Moreover, ζ governs the utility weight on agricultural goods, η governs the elasticity of substitution between agricultural and nonagricultural consumption, and σ governs the intertemporal elasticity of substitution of consumption expenditure.

From age 6 onward, when individuals enter school, they make decisions related to consumption and education investment at each age τ until reaching a terminal age T, denoted $\{c(\tau), e_p(\tau)\}_{\tau \in [6,T]}$. They also decide the age (s) to end schooling, select a work sector, and commence working (hence, $e_p(\tau) = 0$ for all $\tau \in (s, T]$). The utility maximization problem for an individual working in sector i, with initial endowment $\{\psi, l, b\}$, is expressed as:

$$V_i(\psi, l, b) = \max_{c(\tau), e_p(\tau), s, \kappa(s)} \int_6^T e^{-\rho(\tau - 6)} u(c(\tau)) d\tau \tag{2}$$

[13]This is an indirect utility function that depends on the total consumption expenditure $c(\tau)$ and price vectors. Equation (1) emerges from the maximization of the direct utility:

$$\left[\zeta^{\frac{1}{\eta}} (c_a - \bar{c})^{\frac{\eta-1}{\eta}} + (1-\zeta)^{\frac{1}{\eta}} c_m^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}$$

subject to

$$p_a(\tau)c_a(\tau) + p_m(\tau)c_m(\tau) \leq c(\tau)$$

and then substitute the solutions of $c_a(\tau)$ and $c_m(\tau)$ into the direct utility function. This method is commonly used to reduce the dimensionality of the problem (see, e.g., Donovan, 2021; Cheung, forthcoming).

s.t.

$$\int_6^s e^{-r(\tau-6)}[c(\tau)+e_p(\tau)]d\tau + e^{-r(s-6)}\kappa(s) \leq b \tag{3}$$

$$\int_s^T e^{-r(\tau-6)}c(\tau)d\tau \leq \int_s^R e^{-r(\tau-6)}(1-\iota)w_i\left(h(s),\tau-s;\psi,l\right)d\tau + e^{-r(s-6)}\kappa(s) \tag{4}$$

$$h(s) \leq z_h\left[\int_6^s \psi(e_p(\tau)+e_g(\tau))^{\alpha}d\tau\right]^{\frac{\gamma}{\alpha}} \tag{5}$$

$$\kappa(s) \geq 0 \tag{6}$$

$$e_p(\tau) \geq 0 \text{ for all } \tau$$

$$0 \leq s \leq R$$

Equation (3) indicates that individuals face borrowing constraints and are unable to borrow as much as they need based on their future earnings when $\tau < s$.[14] This constraint stems from imperfect credit markets, restricting individuals' borrowing capacity based on their initial wealth. Nevertheless, individuals can save a portion of their initial wealth for future use, denoted as $\kappa(s) \geq 0$.

When $\tau < s$, individuals decide on private education investment, $e_p(\tau)$, as well as consumption and saving. Equation (5) characterizes the factors that influence the accumulation of human capital $h(s)$.[15] These include the economy-wide efficiency in human capital production, z_h, an individual's idiosyncratic ability, ψ, the age at which the individual leaves school, s, and education expenditure over time, $e(\tau)$, made up of private education expenditure, $e_p(\tau)$, and public education expenditure, $e_g(\tau)$. The parameter α determines the degree of intertemporal substitutability of education investment over an individual's school time, and γ governs the scale of returns associated with the total effective education expenditure.

Once individuals enter the workforce, i.e., $\tau > s$, their lifetime income is determined by the discounted present value of their wage income earned through a retirement age R. The

[14] The borrowing constraint in this study refers to limits on individuals' ability to borrow the desired amount during their schooling period, a common assumption in previous research (e.g., Lochner and Monge-Naranjo, 2011). Equation (6) can be generalized to allow for any specific borrowing limit to accommodate student loans. However, as the availability and amounts of student loans vary across countries, explicitly modeling them would require estimating an additional borrowing parameter, for which cross-country dataset is lacking. Hence, we choose a simplified method that assumes no borrowing is allowed. However, since better-developed countries are more likely to offer student loans, assuming a universal nonnegative borrowing constraint results in more conservative estimates of global human capital disparity and the impact of education policy on reducing this disparity. Moreover, as student loans are part of government education policy, and they augment the total funds available to individuals in school, our model partially accommodates student loans through government education subsidies ($e_g(\tau)$) and the initial wealth endowments (b).

[15] We follow Córdoba and Ripoll (2013) in assuming perfect substitution between private and public education expenditures; Kotera and Seshadri (2017) propose an alternative elasticity of substitution. Our theory is robust provided that private and public education expenditures are substitutes.

sectoral wage $w_i(h(s), \tau - s; \psi, l)$ in equation (4) is assumed to follow the functional form

$$w_i\left(h(s), \tau - s; \psi, l\right) = \tilde{w}_i\left(h(s); \psi, l\right) e^{\nu_{1i}(\tau - s) + \nu_{2i}(\tau - s)^2}$$

which depends on both the education and ability $\tilde{w}_i(h(s); \psi, l)$, as well as the experience $e^{\nu_{1i}(\tau-s)+\nu_{2i}(\tau-s)^2}$, consistent with the Mincer equation. The parameters ν_{1i} and ν_{2i} are sector-specific and will be estimated using data from IPUMS (Ruggles et al., 2022). Additionally, we assume that sector-specific experience will be lost when an individual switches sectors.[16] Employed individuals pay a proportional income tax rate, ι. The tax revenue funds public education for current students, $e_g(\tau)$, and funds redistribution of initial wealth, b, to the new entry cohort (i.e., individuals at $\tau = 6$).

Lastly, the determination of the sectoral decision, D, is based on the selection of the sector that maximizes utility. Mathematically, this is represented as $D = \arg\max_{D \in \{0,1\}} \{DV_a(\psi, l, b) + (1 - D)V_m(\psi, l, b)\}$, where $V_a(\psi, l, b)$ and $V_m(\psi, l, b)$ denote the corresponding values attributed to the agricultural and nonagricultural sectors, respectively.

3.2 Financial Constraint and Education

Let λ_1 and λ_2 denote the Lagrangian multipliers associated with equations (3) and (4), respectively. The FOCs for consumption $c(\tau)$ for $\tau \in [6, s]$ and $\tau \in [s, T]$ imply

$$J \equiv \frac{\lambda_1}{\lambda_2} = \frac{u_c(c^S(s))}{u_c(c^W(s))} \geq 1$$

The inequality arises from the non-negative borrowing constraint stated in equation (6). Note that this inequality implies a potential discontinuity in consumption at age $\tau = s$, i.e., $c^S(s) \leq c^W(s)$. If $J > 1$, it indicates that $c^S(s) < c^W(s)$ and the individual is financially constrained. In this case, the individual would have smoothed consumption by borrowing, as indicated by a negative value of $\kappa(s)$. However, due to the non-negativity borrowing constraint, the individual will be compelled to exhaust all the initial wealth b and will not have any savings remaining, implying that $\kappa(s) = 0$.

When $J = 1$, the individual can smooth consumption between the schooling and working periods, so $c^S(s) = c^W(s)$. The savings at age s can be calculated as follows:

$$\kappa(s) = \frac{\frac{b - E^*}{D_6^s} - \frac{I_i(s)}{D_s^T}}{e^{-r(s-6)}\left[\frac{1}{D_6^s} + \frac{1}{D_s^T}\right]} \geq 0$$

[16] According to Herrendorf and Schoellman (2018), only a small fraction (0.45%) of workers switched from the agricultural to the nonagricultural sector between 1968 and 1997 in the U.S.

where E^* represents the discounted present value of private education expenditure, $I_i(s)$ is the discounted present value of wage income during the working period, and D_x^y contains a set of discount factors.[17] The aforementioned expression can be interpreted as follows: the level of saving, $\kappa(s)$, is inversely related to both the cost of private education, E^*, and the amount of future wage income, $I_i(s)$. This is because a higher private education expenditure reduces the initial wealth that can be saved, and higher future income discourages saving during the schooling. Nonetheless, the expression is positively related with initial wealth endowment, b.

The optimal level of schooling is influenced by the value of J, as seen in the following FOC with respect to s. The left-hand side represents the marginal benefit of an additional year of schooling, while the right-hand side represents the marginal cost (when $J > 1$):

$$\begin{aligned}
&\frac{\partial}{\partial s} \int_s^R e^{-r(\tau-6)} w_i\left(h(s), \tau - s; \psi, l\right) d\tau \\
&= \underbrace{J e^{-r(s-6)} \left[\frac{u(c^W(s)) - u(c^S(s)) + u_c(c^S(s))c^S(s) - u_c(c^W(s))c^W(s)}{u_c(c^S(s))} + e_p(s) \right]}_{\text{RHS}}
\end{aligned}$$

When $J = 1$, the right-hand side of this equation becomes $e^{-r(s-6)}e_p(s)$. The utility function in equation (1) implies that $\text{RHS}_{J>1} > \text{RHS}_{J=1}$. This implies that the marginal cost of schooling is higher for individuals with binding budget constraints. Intuitively, all else equal, budget-constrained individuals have higher marginal utility of consumption (due to lower levels of consumption), which increases the utility cost of investing in education. Consequently, they have fewer years of schooling.

3.3 Education Policy and Education

Public education policy is defined as a combination of public education expenditure per pupil per year, $e_g(\tau)$, and the maximum age to receive government subsidies, $\bar{s}$. Let us consider a hypothetical scenario where there is no public education expenditure, i.e., $e_g(\tau) \equiv 0$. In this case, the optimal private education expenditure, $\hat{e}^*(\tau)$, can be expressed as

$$\hat{e}^*(\tau) = \hat{e}(0) e^{\frac{r(\tau-6)}{1-\alpha}}$$

[17] To provide further clarity, the discounted present value of private education expenditure is denoted as $E^* = \int_6^s e^{-r(\tau-6)} e_p(\tau) d\tau$, the discounted present value of wage income is denoted as $I_i(s) = \int_s^R e^{-r(\tau-6)} w_i\left(h(s), \tau - s; \psi, l\right) d\tau$, and the collection of discount factors is denoted as $D_x^y = \int_x^y e^{-r(\tau-6)} \left(e^{(\rho-r)(\tau-6)}\right)^{-\frac{1}{\sigma}} d\tau$.

where $\hat{e}(0) = \left[\left(\psi\gamma z_h^{\frac{\alpha}{\gamma}} h(s)^{1-\frac{\alpha}{\gamma}} \int_s^R e^{-r(\tau-6)} w_i'(h(s), \tau - s; \psi, l) d\tau\right) / J\right]^{\frac{1}{1-\alpha}}$ is predetermined by an individual's endowment and remains unaffected by age, τ. The value of $\hat{e}(0)$ determines the intercept of $\hat{e}^*(\tau)$ at $\tau = 6$. The function $\hat{e}^*(\tau)$ is strictly increasing in τ, indicating that the optimal education expenditure increases as an individual grows older as long as $\tau < s$.

Due to data limitations, it is infeasible to differentiate public education expenditure by age. We thus assume that $e_g(\tau) \equiv e_g$ for $\tau \in [6, \bar{s}]$, and calibrate the value of e_g to match the public education expenditure as a share of GDP. The total expenditure on education for an individual at age τ is the sum of private and public education expenditures at that age, denoted as $e(\tau) = e_p(\tau) + e_g(\tau)$. Taking into account the public education subsidy in personal education investment, we have:

$$e(\tau) = \begin{cases} e_g & \text{for } \min\{s, 6\} \leq \tau \leq s_g \\ \hat{e}^*(\tau) & \text{for } s_g \leq \tau \leq s \end{cases}$$

where $s_g \equiv \min\{s, \bar{s}, s_{ug}\}$ and s_{ug} is defined such that $\hat{e}(s_{ug}) = e_g$. Note that s_{ug} represents the maximum age at which an individual can receive education solely dependent on public education expenditure, subject to the condition that $s_{ug} < \min\{s, \bar{s}\}$.[18] Appendix C provides an example illustrating how the introduction of a public education system affects private education expenditure.

Finally, an individual's human capital is determined by the following equation:

$$\begin{aligned} h(s) &= z_h \psi^{\frac{\gamma}{\alpha}} \hat{e}(0)^\gamma \left[\int_6^{s_g} \left(\frac{e_g}{\hat{e}(0)}\right)^\alpha d\tau + \int_{s_g}^{s} e^{\frac{r\alpha(\tau-6)}{1-\alpha}} d\tau\right]^{\frac{\gamma}{\alpha}} \\ &= z_h \psi^{\frac{\gamma}{\alpha}} \hat{e}(0)^\gamma \left[\left(\frac{e_g}{\hat{e}(0)}\right)^\alpha (s_g - 6) + \frac{1-\alpha}{r\alpha}\left(e^{\frac{r\alpha(s-6)}{1-\alpha}} - e^{\frac{r\alpha(s_g-6)}{1-\alpha}}\right)\right]^{\frac{\gamma}{\alpha}} \qquad (7) \end{aligned}$$

which implies that an individual's human capital is influenced by various factors, including government education policy, the individual's endowment, education investment, and the economy-wide efficacy in human capital production.

To this end, we highlight the role of government education policy in facilitating human capital accumulation. On the one hand, education subsidies reduce individuals' marginal costs of education by relaxing the financial constraint faced by the less wealthy. On the other hand, the subsidies allow for greater accumulation of human capital with the given

[18]The expression for s_{ug} is given by $s_{ug} = ((1-\alpha)/r) \ln(e_g/\hat{e}(0)) + 6$. The value of s_{ug} is negatively related to $\hat{e}(0)$, which depends on an individual's initial endowment. For example, a wealthier individual will be less dependent on the public education system. s_{ug} also satisfies $\hat{e}(s_{ug}) \lesseqqgtr e_g$ if and only if $\tau \lesseqqgtr s_{ug}$. Finally, if $\hat{e}(\tau)$ is greater than e_g for all τ greater than 6, then s_{ug} is set to 6.

private education investment, leading to better quality of education and higher returns to schooling. These effects are further strengthened by a longer duration of subsidies.[19]

3.4 Government

The government collects wage income taxes at a proportional rate ι, and the tax revenue is used for public education and to provide the initial wealth endowment to individuals at age $\tau = 6$. We assume that the government maintains a balanced budget at all times. Let $x = \{\psi, l, b\}$ denote an individual's endowment set. At each period, the following balanced-budget equation holds:

$$N \iint_{s}^{R} \iota w\left(h(s), \tau - s; \psi, l\right) d\Pi(\tau) dG(x) = N \iint_{6}^{s_g} e_g d\Pi(\tau) dG(x) + N_6 \int b dG(x) \qquad (8)$$

where $\Pi(\tau)$ represents the population's age distribution, N represents the measure of the total population and N_6 the measure of population at age 6. The left-hand side of equation (8) represents the total tax revenue collected, and the right-hand side of the equation shows that the tax revenue is fully allocated towards funding public education, e_g, for all individuals below age s_g, and towards endowing new generations with initial wealth.

The incorporation of the government sector into the model allows individuals' initial wealth to depend on the level of economic development in our counterfactual analysis. For example, given the public education expenditure to GDP ratio, a more productive economy (e.g. resulting from exogenous increases in TFP) with higher wage income and tax revenues will generate higher initial wealth for its citizens. This eases individuals' budget constraints and, therefore, increases their investment in human capital.

3.5 Production

To close the model, we introduce the production side of the economy. Both the agricultural and nonagricultural sectors rely on efficiency units of labor, denoted by $\xi_i(h(s); \psi, l)$, as the only input; however, the functional form of the efficiency units differs by sector. Upon finishing school, a worker's efficiency units in the two sectors are given by

$$\xi_a(h(s); l) = \left[\theta_a h(s)^{\frac{1}{\phi_a}} + (1 - \theta_a) l^{\frac{1}{\phi_a}}\right]^{\phi_a}$$

[19]In an general equilibrium framework, an increase in education subsidies could lead to a decrease in years of schooling, since the opportunity costs of schooling (i.e., loss in work time) creates a trade-off between longer schooling duration (quantity) and higher education investment per year (quality). However, our quantitative analysis demonstrates that an improved public education system can lead to an increase in the stock of human capital, even when the years of schooling are reduced.

$$\xi_m(h(s);\psi) = \left[\theta_m h(s)^{\frac{1}{\phi_m}} + (1-\theta_m)\psi^{\frac{1}{\phi_m}}\right]^{\phi_m}$$

While both sectors require human capital, agricultural production relies on an individual's agricultural productivity, l, whereas nonagricultural production relies on ability, ψ. To match the stylized facts, we assume $\theta_m > \theta_a$ to ensure that the nonagricultural sector uses human capital more intensively than the agricultural sector. The parameter ϕ_a (ϕ_m) governs the elasticity of substitution between human capital and agricultural productivity (ability). The total output of sector i, Y_i, is then given by

$$Y_i = A_i N \iint_{\Omega_i} \hat{\xi}_i(h(s);\psi,l) d\Pi(\tau) dG(x)$$

where A_i is the sectoral TFP, Ω_i is the (endogenous) set of individuals who work in sector i, and $\hat{\xi}_i(h(s);\psi,l) = \xi_i(h(s);\psi,l)e^{\nu_{1i}(\tau-s)+\nu_{2i}(\tau-s)^2}$ is the efficiency units of labor embodied in a worker with her experience incorporated. Firms operate in a competitive market and face a wage rate of $\hat{w}_i = p_i A_i$. Therefore, a firm's maximization problem can be formulated as[20]

$$w_i\left(h(s), \tau - s; \psi, l\right) = \hat{w}_i \hat{\xi}_i(h(s);\psi,l) \tag{9}$$

4 Baseline Calibration

We calibrate first the model to reflect the U.S. economy circa 2000, establishing our baseline model. We then adjust certain parameters to represent the U.S. economy circa 1900, as well as for a diverse set of other countries, capturing various income levels across the global distribution. Our primary focus is on analyzing the steady-state equilibrium, which is formally defined in the Online Appendix D.

4.1 Calibration to the U.S. economy in 2000

In order to calibrate the model to reflect the U.S. economy circa 2000, we start by setting certain parameters based on values found in the literature or data. The remaining parameters are then jointly calibrated within the model by minimizing the discrepancy of a set of targeted moments between the model and the data. The major steps of the calibration are detailed below. Table 1 summarizes these parameter values.

Distribution of (ψ, l, b). We denote the cdf of each variable by $G_y(y)$, where $y \in \{\psi, l, b\}$. Assuming that $\{\psi, l, b\}$ follow lognormal distributions, $\ln(y) \sim \mathcal{N}(\mu_y, \sigma_y)$, we

[20] Alternatively, it can be written as $w_i\left(h(s), \tau - s; \psi, l\right) = \tilde{w}_i\left(h(s);\psi,l\right) e^{\nu_{1i}(\tau-s)+\nu_{2i}(\tau-s)^2}$, where $\tilde{w}_i\left(h(s);\psi,l\right) = \hat{w}_i \xi_i(h(s);\psi,l)$.

Parameters	Value	Target
Panel A: Predetermined		
Talent	$\mu_\psi = \mu_l = 1$	Normalize
Preference	$\rho = 0.03$, $\zeta = 0.005$, $\sigma = 1.5$, $\eta = 0.85$	Preset or Literature
Human capital	$z_h = 1$, $\bar{s} = 18$	Normalize or Data
Experience	$\nu_{1,a} = 0.0254$, $\nu_{2,a} = -0.0004$, $\nu_{1,m} = 0.0382$, $\nu_{2,m} = -0.0006$	IPUMS USA
Production	$A_a = 1$	Normalize
Life exp. & retirement	$T = 76.6$, $R = 65$	Data
Panel B: Calibrated		
Preference	$\bar{c} = 0.15$	1. Agri. Wage Gap, 2. Var. Agr. Wage, 3. Var Non-agr. Wage,
Production	$A_m = 0.37$, $\theta_m = 0.80$, $\phi_m = 4.78$, $\theta_a = 0.75$, $\phi_a = -2.65$	4. Agr. Emp. Share, 5. Agr. V.A. Share, 6. Agr. School Years, 7. Non-Agr. School Year, 8. Private Exp. on School,
Talent/ Wealth	$\sigma_\psi = 0.44$, $\sigma_l = 0.45$, $\rho_{\psi l} = 9.64$, $\mu_b = 5.31$, $\sigma_b = 0.66$	9. Public Exp. on School, 10. Agr. Return to School, 11. Non-agr. Return to School, 12. Wealth-Wage Ratio,
Human capital	$\alpha = 0.26$, $\gamma = 0.27$, $e_g = 5.34$	13. S.D. log Wealth, 14. Non-agr. Price Gap

Table 1: Summary of Parameter Values, U.S. 2000 (Baseline).

assume the interdependence between ψ and l as suggested by Lagakos and Waugh (2013). Thus, the joint distribution of $\{\psi, l, b\}$ can be expressed as $G(\psi, l, b) = G_{\psi l}(\psi, l; \rho_{\psi l}) \cdot G_b(b)$, with $G_{\psi l}(\psi, l; \rho_{\psi l})$ denoting the joint distribution of (ψ, l), and the parameter $\rho_{\psi l}$ determining their interdependence, modeled using the Frank copula. We set the mean values of ψ and l to 1 (so that the log values are 0), calibrating the values of σ_ψ, σ_l, $\rho_{\psi l}$, μ_b, and σ_b within the model to align with sectoral wages and relevant wealth-related moments.[21]

Production. We set $A_a = 1$ and calibrate A_m, θ_m, θ_a, ϕ_m, and ϕ_a within the model.

Preference. In line with prevailing macroeconomic literature, we choose a subjective discount rate of $\rho = 0.03$. To reflect the long-term agricultural employment share of around 0.5%, the parameter ζ is set at 0.005. Following Cooley and Prescott (1995), we assign a value of 1.5 to the reciprocal of the intertemporal elasticity of substitution (σ). Following Herrendorf, Rogerson and Valentinyi (2013), we set the elasticity of substitution between agricultural and nonagricultural goods consumption (η) at 0.85, indicating that they are gross complements. Lastly, the parameter $\bar{c}$ is calibrated within the model.

Human capital and experience. For the human capital production function, z_h is set to 1, with α and γ calibrated within the model. We use UNESCO (2023) and World Bank (2023) to set $\bar{s}$ at 18, representing the end of compulsory education in the U.S., and calibrate e_g to match the ratio of public education expenditure to GDP.

Using data from the 2000 U.S. Census provided by IPUMS, we estimate the return to experience in each sector, finding that it is higher in the nonagricultural sector ($\nu_{1,m} = 0.0382$ and $\nu_{2,m} = -0.0006$) than in the agricultural sector ($\nu_{1,a} = 0.0254$ and $\nu_{2,a} = -0.0004$).

[21] We discretize the distributions of ψ and l into 20 levels each, with cdfs ranging from 0.025 to 0.975 and intervals of 0.05. Additionally, the distribution of b is discretized into 5 levels, with a cdf ranging from 0.1 to 0.9 and intervals of 0.2, resulting in 2000 individual types within the model economy. We solve the model for each type and compute the aggregate moments.

These values describe the connection between experience and wage growth.[22]

Life span and retirement age. By matching U.S. life expectancy circa 2000, as reported by World Bank (2023), we set the life span T to 76.6, and the retirement age R to 65.

Joint Calibration. We have 14 remaining parameters to calibrate within the model: A_m, θ_m, θ_a, ϕ_m, ϕ_a, σ_ψ, σ_l, $\rho_{\psi l}$, μ_b, σ_b, $\bar{c}$, α, γ, and e_g. These parameters are jointly calibrated to match 14 moments from the data: the sectoral wage gap (w_m/w_a), sectoral (log) wage variance $(\text{Var}(w_a), \text{Var}(w_m))$, agricultural employment share (L_a/L), agricultural value-added share (p_aY_a/Y), sectoral years of schooling (s_a-6, s_m-6), private and public education expenditures to GDP ratios $(E_p/Y, E_g/Y)$, sectoral return to schooling $(\partial w_a/\partial s_a, \partial w_m/\partial s_m)$, wealth-income ratio, standard deviation of (log) wealth at the beginning of the work year $(W_i/w_i, \text{SD}(\ln(W_i)))$, and sectoral price ratio (p_m/p_a).

To provide context for these moments, we refer to various studies and data sources. The sectoral wage gap and wage variance are estimated by Lagakos and Waugh (2013) using the non-transitory component of log wages from CPS data between 1996 and 2010. Gollin, Lagakos and Waugh (2014) provides data on the agricultural employment share, value-added share, and sectoral years of schooling. The private and public education expenditure shares are obtained from World Bank (2023).

In terms of the sectoral return to schooling, we adopt estimates from Angrist and Keueger (1991) that correct for selection bias. The return to schooling in the nonagricultural sector is set at 7.5%, while that in agriculture is set at 5%. These values align with estimates from U.S. census data, suggesting that the return to schooling in non-agriculture is higher than in agriculture.[23]

For wealth-related moments, we rely on data from PSID spanning 1999 to 2019. Specifically, we compute the wealth-income ratio and the standard deviation of log wealth at the beginning of the working age using net worth and labor income data on individuals aged 24 to 29.[24] Finally, the sectoral price ratio is obtained from Alvarez-Cuadrado and Poschke (2011), who provide information on the relative prices of agricultural and nonagricultural goods. The values of the targeted moments are summarized in Table 2.

[22] In our analysis, we assume that the return to experience is constant across different countries due to data limitations. However, evidence suggests that wage-tenure profiles in developing countries are relatively flatter (Lagakos et al., 2018), indicating a smaller return to experience compared to developed countries. Incorporating this consideration would further support our findings by reducing the efficiency unit of labor in developing countries.

[23] According to estimates based on U.S. census data from various years, the return to schooling in non-agriculture sectors is approximately 40–50% higher than the return to schooling in the agricultural sector.

[24] To handle negative wealth values, we set them to $1e-6$ when calculating the standard deviation of log wealth.

4.2 Model Fit

Table 2 presents the goodness of fit, which demonstrates that the model fits the targeted moments well.

Target	Numerically	Data	Model
Agri. Wage Gap	w_m/w_a	1.43	1.49
Var. Agr. Wage	$Var(w_a)$	0.14	0.15
Var. Nonagr. Wage	$Var(w_m)$	0.22	0.22
Agr. Emp. Share (%)	L_a/L	1.50	1.54
Agr. VA. share (%)	p_aY_a/Y	1.10	1.04
Agr. School Years	$s_a - 6$	11.55	11.01
Nonagr. School Years	$s_m - 6$	13.18	13.99
Private Exp. on School (%)	E_p/Y	2.10	1.96
Public Exp. on School (%)	E_g/Y	4.95	4.96
Agr. Return to School	$\partial w_a/\partial s_a$	0.050	0.052
Nonagr. Return to School	$\partial w_m/\partial s_m$	0.075	0.070
Wealth-Income Ratio	W_i/w_i	2.45	2.01
S.D. log Wealth	$SD(ln(W_i))$	11.41	11.75
Price Ratio	p_m/p_a	1.60	1.60

Table 2: Model Fit, U.S. 2000 (Baseline).

The accuracy of the calibrated model is assessed by comparing it with the model-based distribution of sectoral years of schooling, as illustrated in Figure 5. Although the calibration does not specifically target this distribution, the model aligns well with the years of schooling distribution within each sector, particularly in the nonagricultural sector. In the agricultural sector, the model is consistent with the data regarding the distribution of schooling years but does not fit as robustly as in the nonagricultural sector. Specifically, the model predicts a lower level of variance in the years of schooling distribution compared to the data.

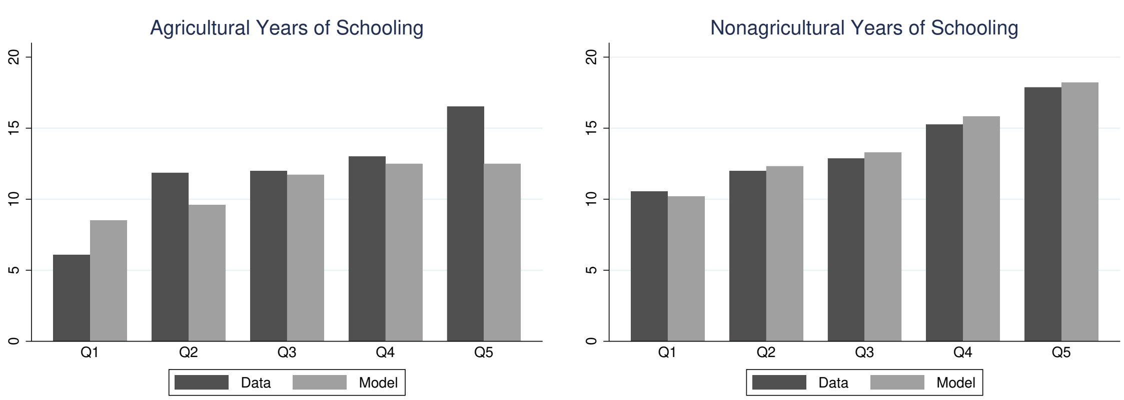

Figure 5: Sectoral Years of Schooling by Quintile, Model vs. Data.

5 Quantitative Analysis and Discussion

We now use the calibrated model to explore differences in human capital, agricultural employment share, and labor productivity, across time and nations. We show that education policies significantly contribute to the variations in human capital accumulation and agricultural employment observed across different periods and countries.

5.1 The United States: 1900s versus 2000s

To gain insights into the U.S. structural transformation over the past century and the role human capital accumulation has played in this process, we recalibrate our model to reflect the U.S. economy circa 1900. Specific adjustments are made to parameters relating to life expectancy, wealth distribution, compulsory years of schooling, public education expenditure, and production technology, while other parameters remain unchanged from the baseline economy. The calibrated parameters for the U.S. 1900 scenario are summarized in Table A.1.

Specifically, to calibrate to the U.S. economy of the 1990s, we follow Manuelli and Seshadri (2009) to set life expectancy at $T = 52$. We calibrate the sectoral productivity parameters (A_a, A_m) and the human capital intensity parameters (θ_a, θ_m) using temporal GDP per worker to the U.S. 2000s ratio from Manuelli and Seshadri (2009), agricultural value-added shares from Caselli and Coleman (2001), and temporal sectoral output per worker ratios from Chen (2020). We set education expenditure (e_g) so that public education expenditure represents approximately 1% of GDP and set the average duration of compulsory schooling to 3.6 years; thus, $\bar{s} = 9.6$.[25] We back out the initial wealth distribution (G_b) using GDP per capita, wealth-income ratio, and top wealth concentration from Piketty and Saez (2014).[26] The latter indicates a decline in top 10% wealth concentration from 79% around 1900 to 68% in 2000. The goodness of fit between the model and the data is demonstrated in Table A.2, showing close alignment in the targeted moments between the model and the data.

Furthermore, we examine several untargeted moments to assess the model's ability to account for changes observed over the past century. We show that the model provides reasonable predictions for schooling and agricultural employment shares. Specifically, Table 3 reveals that the model predicts a 7.2-year increase in years of schooling, while the actual data indicates a 7.8-year increase, accounting for 92% of the observed rise. Additionally, the model

[25]For public education expenditure around 1900, the nominal GNP was around 19 billion (U.S. Bureau of the Census, 1975, Series F1), and the nominal expenditure on public schools was around 0.2 billion (Snyder, 1993, Table 22). Additionally, 31 states mandated 6 years of compulsory schooling (Goldin and Katz, 2010) while the rest had no compulsory schooling. Thus, the simple average number of compulsory schooling years was about 3.6 years around 1900.

[26]We follow a similar method to estimate the wealth distribution for the U.S. 1900 as for other countries; see Section 5.2 for details.

predicts a 21.9 percentage-point reduction in agricultural employment share, whereas the data shows a 37.5 percentage-point reduction, accounting for 58% of the observed decrease.

	Data		Model		$\{e_{g,1900}, \bar{s}_{1900}\} = \{e_{g,2000}, \bar{s}_{2000}\}$	
	2000	1900	2000	1900	PE	GE
Years of Schooling	13.2	5.4	13.9	6.7	7.4	7.0
Agricultural Employment Share (%)	1.5	39.0	1.5	23.4	5.8	19.5
Human Capital (Normalized)	.	.	4.1	1.0	2.0	1.9

Table 3: United States 1900 and 2000.

Next, we explore how public education policy drives human capital accumulation and structural transformation by applying the more favorable education policy from the 2000s to the 1900s.[27] Our simulation shows that, when keeping prices constant, education policy accounts for 31% of the variations in human capital between the two periods. It also accounts for 81% of the decline in the agricultural employment share from 1900 to 2000. Nevertheless, the influence of education policy is moderated by the general equilibrium mechanism. Increases in human capital make the nonagricultural sector more productive relative to the agricultural sector, thereby increasing the relative price of agricultural goods (due to the complementarity of agricultural and nonagricultural goods in consumption) and lowering nonagricultural wages relative to agricultural ones (see Goldin and Margo, 1992, for the concept of wage compression). This shift decreases the demand for schooling and increases agricultural employment compared to a partial equilibrium. Still, even considering these attenuation effects, the general equilibrium mechanism does not substantially undermine the policy's impact on human capital accumulation. Specifically, under general equilibrium, the education policy can still explain 28% of the increase in human capital and 18% of the structural transformation in the model. Provided that our model explains 58% of the decline in agricultural employment share, we conclude that education policy is responsible for approximately 10% of the observed structural transformation over the past century.

5.2 Cross-Country Analysis

We now examine cross-country variations in schooling and structural transformation, as well as the role of public education policy in shaping them. To accomplish this, we set the parameters concerning life expectancy, wealth distribution, compulsory years of schooling, and public education expenditure to match country-specific data. Additionally, we recalibrate

[27]We do not change the tax rate, however, because the 2000 education system would be unaffordable in 1900 if funded by income taxes. We focus on the effects of education policy rather than taxation.

the parameters associated with sectoral TFP and human capital intensity for each country. The calibration process aligns country-specific indicators like GDP per worker relative to the U.S., agricultural output per worker relative to the U.S., and sectoral years of schooling, all around the year 2000. We select 20 countries, including the U.S., that are separated by exactly 5 percentiles in income distribution, to ensure a diverse representation of countries.[28]

The life expectancy data is from World Bank (2023) and years of compulsory schooling is from UNESCO (2023).[29] Public education expenditure of a specific country (e_g) is determined using the public expenditure to GDP ratio from World Bank (2023). To estimate the distribution of initial wealth, G_b, we use GDP per capita, the wealth-income ratio, and top 10% wealth concentration data for specific countries and the U.S., using the U.S. value as the reference.[30] The sectoral productivity parameters (A_a, A_m), and the human capital intensity parameters (θ_a, θ_m) are calibrated to match the GDP per worker and agricultural output per worker relative to the U.S., as well as sectoral years of schooling.[31]

5.2.1 Model Validity

The model fit is evaluated using the agricultural employment share and human capital stock, neither of which are targets of the calibration exercise. To construct the human capital measure from data, we employ the approach outlined by Schoellman (2012). Specifically, we posit that a country's human capital stock takes the following form:

$$H = \exp\left[\frac{(SQ)^{\phi}}{\phi}\right]$$

where S denotes the years of schooling, and Q corresponds to the returns to schooling. Additionally, ϕ is assigned the value of 0.5, following Schoellman (2012). Human capital stocks obtained from the model, based on Equation (5), and those acquired from the data, are standardized and transformed into standard scores for comparison. This adjustment is

[28] The choice of 20 countries, instead of the full sample, is driven by computational limitations. The list of countries is available in Table A.3.

[29] The retirement age is set at 65, the same as in the United States, given that individuals in developing countries often work until later stages of their lives when $T \leq R$.

[30] Specifically, we calculate the wealth distribution parameters μ_b and σ_b for each country using two conditions. First, the mean value of b for country i is derived as $E_i(b) = e^{\mu_{b,US}+\sigma^2_{b,US}/2} \cdot \frac{W_i/w_i}{W_{US}/w_{US}} \cdot \frac{\tilde{y}_i}{\tilde{y}_{US}}$. Second, we assume that the top 10% wealth concentration of a country relative to the U.S. implied by the model aligns with the data. The wealth-income ratio W_i/w_i and top 10% wealth concentration data are from Alvaredo et al. (2023), and GDP per capita $\tilde{y}_i$ is from Gollin, Lagakos and Waugh (2014).

[31] We obtain GDP per worker (at PPP) relative to the U.S. and sectoral years of schooling from Gollin, Lagakos and Waugh (2014). To compute the agricultural output per worker to U.S. ratio, we construct agricultural value added at internationally comparable prices using data from World Bank (2023) and FAO (2023) (see Online Appendix B for details).

necessary to reconcile the inherent differences in units between the model-based results and the observed data.

The model successfully replicates the observed trends in both the agricultural employment share and human capital stock, as illustrated in Figure 6. The fitted model values align closely with the empirical data, exhibiting statistically insignificant deviations from the 45-degree line. Detailed statistics pertaining to the model's performance can be found in Table A.3. Notably, even without incorporating varying efficiency levels in education (i.e., we set $z_h = 1$ throughout the analysis), the model effectively predicts a country's human capital by leveraging only educational and macroeconomic parameters.

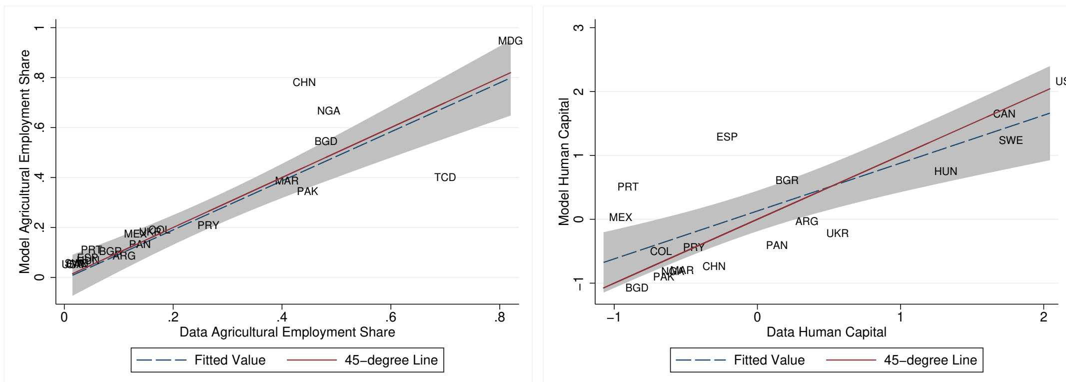

Figure 6: Cross-Country Analysis: Model vs. Data. Note: The gray region signifies a 95% confidence interval.

As most deep parameters are calibrated to 2000s U.S., we now establish the applicability of our calibrated model to educational attainment and agricultural employment trends in developing countries. Our subsequent analysis is centered around Ghana and Indonesia, both of which benefit from comprehensive data acquired through field or natural experiments, as documented by Duflo (2001), Duflo, Dupas and Kremer (2021), and Porzio, Rossi and Santangelo (2022). Our primary objective is to compare the outcomes produced by our model against the results of these empirical experiments, thereby validating the applicability of our model to developing countries.

To begin, we explore the impact of scholarships on the duration of education within our model, and compare it against the outcomes of a randomized experiment conducted in Ghana by Duflo, Dupas and Kremer (2021).[32] The field experiment involved providing secondary school scholarships to a sample of randomly selected junior high students who were eligible for senior high school. To facilitate comparison, we recalibrate our model to

[32]Fujimoto, Lagakos and VanVuren (2023) have used a structural model to investigate the consequences of a nation-wide policy of free secondary schooling on the accumulation of human capital and economic growth.

the context of Ghana, using the same methodology applied to other countries. By extending the subsidized schooling duration within our model by three years, holding prices constant, to replicate the experimental setup, individuals who had completed junior high saw their education increased by 1.04 years. This closely mirrors the 1.25-year increase observed by Duflo, Dupas and Kremer (2021). Consequently, our model effectively generates the observed increase in years of schooling induced by the experiment.

Similarly, we explore the effects of Indonesia's INPRES school construction program, following the studies of Duflo (2001) and Porzio, Rossi and Santangelo (2022). This initiative involved the establishment of 61,000 primary schools between 1974 and 1978. Porzio, Rossi and Santangelo (2022) find that an additional year of schooling induced by the program reduces the likelihood of engaging in agricultural employment by 6.3 percentage points.

To conduct a similar inquiry, we recalibrate our model to the conditions prevailing in Indonesia in 1970. Given that there are no direct model parameters equivalent to the policy changes introduced by this reform, we perform simulations by increasing the years of subsidized schooling by 1, 3, and 5 years, respectively. Subsequently, we calculate the average impact of these increments in schooling on the proportion of individuals employed in the agricultural sector. Our findings indicate that an extra year of schooling leads to an 8.0 percentage point reduction in the agricultural employment share within our model. Consequently, the model effectively replicates the observed relationship between education and agricultural employment share.

5.2.2 Implications for Cross-Country Agricultural Employment Share

In this subsection, we explore how education policy explains cross-country differences in human capital and agricultural employment share. We conduct two experiments to eliminate disparities in public education policy across countries. In the first experiment, we remove the public education policy for all countries by setting the education subsidy to zero. This leads to an average decrease of 27% in human capital stock and a 13% increase in the agricultural employment share across countries. In the second experiment, we impose the U.S. public education system (as of 2000) on all countries in the model by setting $\{e_g, \bar{s}\}_i = \{e_g, \bar{s}\}_{\text{USA}}$.[33] This leads to an average increase of 47% in human capital stock and a 8% decrease in the agricultural employment share across countries. Figure 7 shows the effects of two policies across income distribution.

While both experiments eliminate disparities in education policy across countries by

[33]Note that here we do not allow the tax rate for each country to change, since some low-income countries cannot possibly levy enough tax revenue, and we want to focus on the effect of education policy rather than taxation. This policy can be thought of as international humanity funds for education.

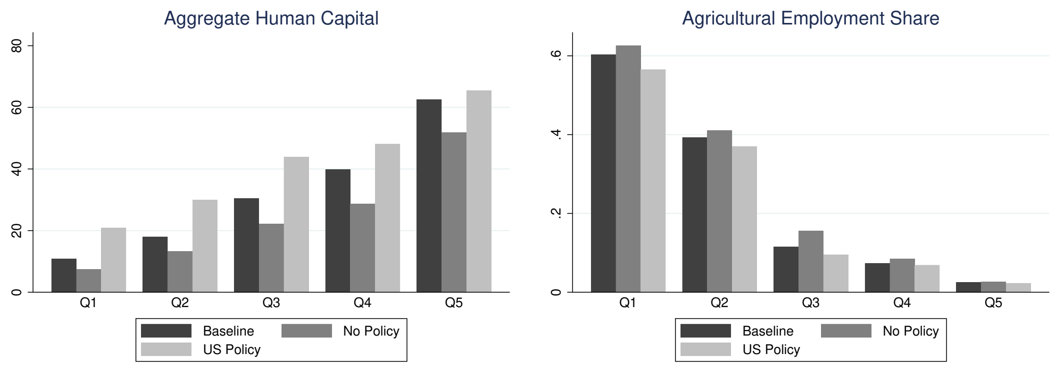

Figure 7: Importance of Public Education System, by Income Quintile.

design, they generate distinct outcomes regarding cross-country *variations* in human capital stock and agricultural employment share. When the U.S. education policy is imposed on all countries, the standard deviation of (log) human capital among the 19 non-U.S. countries decreases from 0.64 to 0.44 (a 31% reduction), and the standard deviation of agricultural employment share decreases from 0.26 to 0.24 (a 6% reduction). Conversely, when the education policy is removed, the standard deviation of (log) human capital increases to 0.71, and that of agricultural employment share increases to 0.27. In other words, improving the public education system narrows human capital disparities across countries, while eliminating the system appears to exacerbate them.

This can be attributed to people in low-income countries relying more on the public education system for education, as it is expensive relative to their income and the return on schooling, whereas people in high-income countries can invest more in education privately. Thus, eliminating the public education system might not create as significant an impact on human capital stock in the high-income countries. Therefore, the results suggest that establishing more advanced public education systems worldwide is vital for reducing global human capital inequality.[34] Given the linkage between human capital accumulation and structural transformation, universally adoption of better education systems would lessen the gap in structural transformation between rich and poor countries.

To explore this linkage, we provide estimates regarding the elasticity of agricultural employment share with respect to human capital or years of schooling. The first experiment

[34]In terms of (log) GDP per worker, however, both experiments in this subsection tend to close the gap across countries, even though removing education policy widens the human capital gap. This is because countries adopt different production technologies, and high-income countries rely more on human capital than do low-income countries. Thus, eliminating public education tends to have a more substantial negative impact on output per worker in rich countries than in poor countries. This reverse some effects on increase in the standard deviation of (log) human capital due to elimination of public education.

above (the removal of public education policy) results in an elasticity of -0.47, while the second experiment (all countries adopt the U.S. education policy) yields an elasticity of -0.17. This discrepancy arises from our closed-economy assumption, which necessitates a certain level of agricultural employment to meet subsistence needs, and creates downward rigidity in agricultural employment share. This linkage, however, is more robust in low-income countries (i.e., those in the first quintile of the income distribution) where the agricultural employment shares are higher. When setting their education system to the U.S. standard, we estimate that the implied elasticity of agricultural employment share with respect to years of schooling is -1.42. This estimate is very close to that of Porzio, Rossi and Santangelo (2022), who studied the effects of the INPRES school construction program (Duflo, 2001) in Indonesia and found the elasticity to be -1.36.

5.2.3 Implications for Cross-Country Productivity Difference

To explore how education policy affects cross-country productivity differences, we conduct two counterfactual experiments. These experiments set each country's education expenditure per year per pupil and years of subsidized schooling, separately, to the U.S. values for 2000. We then document the percentage change in GDP per worker for each country in both experiments. The results are illustrated in Figure 8.

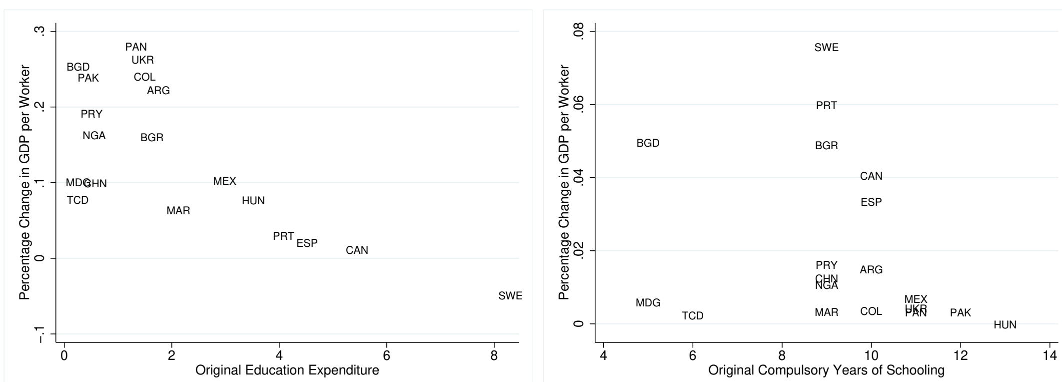

Figure 8: Counterfactual Experiment. Left Panel: e_p; Right Panel: $\bar{s}$.

Two features in Figure 8 warrant discussion. The first notable feature is that the effect of adopting the U.S. education policy on GDP per worker diminishes with a country's original education expenditure and years of subsidized schooling. This is intuitive, as larger education expenditures and more years of subsidized schooling originally make the country more similar to the U.S., so that adopting the U.S. education policy causes smaller changes. This observation indicates convergence in labor productivity across countries, since poorer countries with less advanced education systems would benefit more from adopting the U.S. education policy. For example, the GDP per worker of the country in the 90th percentile of the income distribution (i.e., Sweden) is 24.5 times that of the 10th percentile country (i.e., Bangladesh), but the gap falls to 18.5 times (i.e., a 24% reduction) after both countries adopt the U.S. education policy. The standard deviation of (log) GDP per worker across the 19 non-U.S. countries also decreases from 1.09 to 1.06 when they all adopt the U.S. education policy.

The second notable feature is that the impact of equalizing education expenditure is much more pronounced compared to equalizing years of subsidized schooling. This phenomenon results from two factors. First, cross-country differences in compulsory years of schooling are not as substantial as variations in education expenditure. The gap between the maximum and minimum compulsory years of schooling among our sample countries is 8 years (or 2.6-fold), while the disparity between the maximum and minimum public education expenditure per pupil per year is 33-fold. Naturally, equalizing years of subsidized schooling would not lead to as significant an impact as equalizing education expenditure across countries. Second, people in most countries are not very responsive to increased years of subsidized schooling. The average increase in schooling years as a result of increased subsidized schooling years is 0.39 years on average for all 19 non-U.S. countries and only 0.17 years for the 10 lower-income countries in our sample, even though the latter experience a greater increase in subsidized years of schooling in the experiment. The elasticity of schooling years with respect to subsidized schooling years is 0.22 on average for the 19 non-U.S. countries and only 0.10 for the lower-income countries. This result suggests that, given the return to education and the opportunity cost of schooling (i.e., loss in work years), many individuals' choices on how long to spend in school have already been close to optimal, even with the existing education policy.[35]

5.2.4 The Importance of Education Policies

The literature has long emphasized the importance of technological progress in driving structural transformation through both productivity and income effects. In this subsection, we shift our focus to the distinct mechanism of education policy in shaping structural transfor-

[35]The impact of Ghana's free secondary school policy on years of schooling seems to be larger, as shown in Section 5.2.1. This is primarily because in that experiment, we examine how the extended subsidized years of schooling affects schooling decisions of individuals who have completed 9 years of education, while in this subsection, we focus on the policy impact on an average individual in the country. A three-year extension of subsidized schooling in Ghana results in 1.04-year increase of education for the former group while only 0.08-year increase for the latter one. Therefore, our analysis suggests that an extension of subsidized education has a much larger impact on individuals who are situated at the margin of the school decision at their maximal subsidized age compared to an average individual.

mation.

To investigate this, we quantify the changes required in agricultural and nonagricultural TFP, A_a and A_m, respectively, to match the agricultural employment share that would be reached if a country adopted the U.S. education policy. We find that, for the set of low-income countries (i.e., those in the first quintile of the income distribution), agricultural TFP must increase by 4.2% on average, alternatively, nonagricultural TFP must increase by 10.7%, to achieve the same agricultural employment share as under the U.S. education policy. The requirement for an agricultural TFP increase is lower because it also eases the subsistence constraint in agricultural consumption.

While these changes produce the same agricultural employment share, their implications for labor productivity differ. A 4.2% increase in A_a or a 10.7% increase in A_m would raise GDP per worker by 2.8% and 4.5%, respectively, on average among the low-income countries. In contrast, adopting the U.S. education policy would yield a more substantial increase in GDP per worker – by 17.3% – which is 3.8 and 6.2 times the increase under the technological progress scenario.

This discrepancy arises from the role of human capital. Increases in sectoral TFP lead to sectoral labor reallocation through both the productivity channel (i.e., an increase in A_a eases the subsistence constraint, and an increase in A_m attracts workers to the more productive nonagricultural sector) and the income channel (i.e., income growth reduces the relative demand for food). These changes, however, exert minimal effects on human capital accumulation. Conversely, adopting the U.S. education policy could nearly double a poor country's human capital, having a much more significant impact on labor productivity in the long-run.[36]

6 Conclusion

Public education policy plays a pivotal role in determining a country's human capital accumulation and thereby its structural transformation. We present empirical evidence demonstrating that economies with better education policies experience higher education attainment and labor productivity, and a lower agricultural employment share. Since human capital is relatively more valuable in the nonagricultural sector, individuals with more human capital tend to work outside of agriculture, thus facilitating structural transformation. Moreover, as

[36]For the lower-income countries, on average, a 4.2% (10.7%) increase in A_a (A_m) would increase the human capital stock by 2.2% (3.4%), while adopting the U.S. education policy would increase human capital stock by 93.5%. Evaluating the cost-effectiveness of different policies is, however, complex due to the lack of detailed cost information on policies that increase A_a or A_m. Therefore, a comprehensive cost-benefit analysis comparing the efficiency of education versus industrial policies falls outside the scope of this paper.

human capital acts as a productive input, an increase in human capital enhances a nation's income, reinforcing structural transformation through the income effect.

We consider the quantity and quality of education: quantity refers to the years of schooling; quality refers to the amount of human capital imparted per year of schooling. Two facets of education policy – years of government-subsidized schooling and government expenditure on public education – play key roles in determining education's quantity and quality.

We devise a life-cycle model featuring heterogeneous agents who decide on schooling duration, education expenditures, and sectoral employment, within a multi-sector general equilibrium framework. The model is calibrated for the U.S. in the years around 2000 and 1900, as well as for various countries with different income levels. It successfully replicates both temporal and cross-sectional differences in human capital and agricultural employment share. We estimate that public education policy alone accounts for approximately 10% of observed structural transformation in the U.S. over the past century. Cross-sectionally, our findings show that, while implementing the U.S. education policy universally closes disparities in human capital and agricultural employment share across countries, eliminating it would widen these gaps. These results underline the essential role that education policy plays in reducing global human capital inequality and spurring structural transformation in low-income nations.

Additionally, we explore how education policy drives structural transformation, contrasting it with industrial policies that directly enhance sectoral TFP. Our model illustrates that, although improving education policy and technological advancement can lead to a similar level of structural transformation, their effects on labor productivity differ significantly. Education policy, by enhancing human capital, tends to exert a more profound impact on labor productivity than industrial policies in the long-run.

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Appendix: Human Capital and Structural Transformation

– For Online Publication

A Additional Figures and Tables

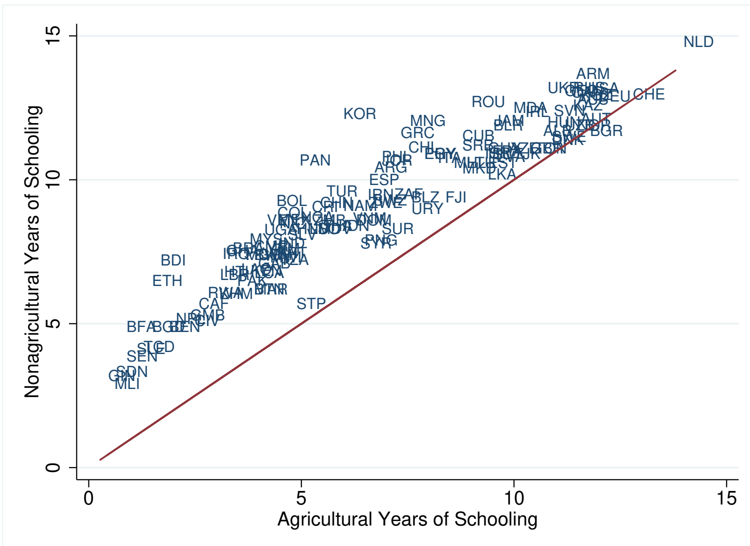

Figure A.1: Schooling Gap

Parameters	Value	Target
Panel A: Predetermined		
Human capital	$\bar{s} = 9.6$	Goldin and Katz (2010)
Life exp.	$T = 52$	Manuelli and Seshadri (2009)
Wealth	$\mu_b = 2.60$, $\sigma_b = 0.85$	World Inequality Database and Piketty and Saez (2014)
Panel B: Calibrated		
Human Capital	$e_g = 0.30$	1. GDP per worker to U.S. 2000 Ratio 2. Agr. V.A. Share
Production	$A_a = 0.15$, $A_m = 0.33$, $\theta_a = 0.16$, $\theta_m = 0.34$	3. Public Education Expenditure to GDP Ratio 4. Agr. Output per worker to U.S. 2000 Ratio 5. Nonagr. Output per worker to U.S. 2000 Ratio

Table A.1: Summary of Parameter Values, U.S. 1900

Target	Variable	Data	Model
GDP per worker to U.S. 2000 Ratio	y_{1900}/y_{2000}	0.14	0.12
Ag. Value-Added Share (%)	$p_a Y_a / Y$	19.0	18.4
Public Education Expenditure to GDP Ratio (%)	E_g/Y	1.00	1.03
Ag. Output per worker to U.S. 2000 Ratio (%)	$y_{a,1900}/y_{a,2000}$	0.03	0.03
Nonag. Output per worker to U.S. 2000 Ratio (%)	$y_{m,1900}/y_{m,2000}$	0.14	0.13

Table A.2: Model Fit, U.S. 1900

Country	Percentile	Ag. Employment Share (%)		Years of Schooling	
		Data	Model	Data	Model
MDG	5	82.0	91.8	4.1	3.7
BGD	10	48.1	50.7	4.3	4.5
TCD	15	70.0	36.4	1.8	3.4
NGA	20	48.6	63.0	6.2	5.7
PAK	25	44.7	30.8	5.1	5.4
MAR	30	40.9	35.0	4.0	4.2
PRY	35	26.5	17.1	7.6	8.3
CHN	40	44.1	74.5	6.4	5.6
UKR	45	15.8	14.6	12.4	7.8
COL	50	17.5	15.4	7.2	6.2
PAN	55	13.9	9.5	9.5	6.9
BGR	60	8.5	6.8	11.7	11.5
ARG	65	11.0	4.9	9.7	8.3
MEX	70	13.1	13.7	7.5	7.6
HUN	75	4.4	3.1	10.3	10.5
PRT	80	5.0	7.4	7.2	8.5
ESP	85	4.3	4.1	9.6	11.0
SWE	90	2.3	2.0	11.5	10.0
CAN	95	2.4	1.5	12.9	12.4
USA	98	1.5	1.5	13.2	13.9
Correlation		0.9		0.9	

Table A.3: Cross-Country Analysis: Model Fit

B Data Appendix

Sample. We begin with Gollin, Lagakos and Waugh (2014) and exclude countries without information on sectoral years of schooling, resulting in a sample of 125 countries.

Life Expectancy. Data is obtained from World Bank (2023) for the year 2005. Specifically, the data series for life expectancy is defined as "Life expectancy at birth, total (years)".

Schooling Policy. We sourced the year of compulsory schooling from UNESCO (2023) for the year 2005. The relevant information can be found in the "Education" section of the report, under "Official entrance age and theoretical duration by level of education (years)," followed by "Theoretical duration," and "Duration by level of education." We utilized the data series entitled "Duration of compulsory education (years)" for our analysis. For our measure of government education expenditure, we used data from World Bank (2023) for the year 2005. If data for 2005 is unavailable, we substitute data from nearby years, with the specific years documented.

Wealth Inequality. We employ two metrics from Alvaredo et al. (2023) to determine wealth inequality. The first metric measures wealth concentration relative to national income, known as "Net Private Wealth to Net National Income Ratio." The second metric measures absolute wealth concentration, known as "Net personal wealth, Top 10%."

National Output. We use two measures to determine the national output level. The first measure, GDP per capita, obtained from the series "GDP per capita (PPP)" in the year 2005 from Gollin, Lagakos and Waugh (2014). The second measure, GDP per worker, requires us to establish the relationship between population and workers using data from World Bank (2023) on "Population ages 0-14 (% of total population)" and "Employment to population ratio, 15+, total (%) (modeled ILO estimate)" for the year 2005. From this information, we calculate GDP per worker, Y/L, using

$$\frac{Y}{L} = \frac{Y}{N} \times \frac{N}{N_{15+}} \times \frac{N_{15+}}{L}$$

where N_{15+}/N is 1 minus "Population ages 0-14 (% of total population)" and L/N_{15+} is "Employment to population ratio, 15+, total (%) (modeled ILO estimate)."

Sectoral Productivity. We estimate sectoral labor productivity as:

$$\frac{Y_i/Y}{N_i/N} = \frac{Y_i}{N_i} \times \frac{N}{Y} \iff \frac{Y_i}{N_i} = \frac{Y_i/Y}{N_i/N} \times \frac{Y}{N}$$

where Y_i/N_i is sectoral labor productivity, Y/N is GDP per worker, Y_i/Y is the sectoral value-added share, and N_i/N is the sectoral employment share. Using data from World Bank (2023) and Gollin, Lagakos and Waugh (2014), we estimate a measure for sectoral labor productivity, Y_i/N_i.

The process to compute a measure of sectoral productivity that is comparable across countries and time periods is detailed and includes steps such as obtaining agricultural value-added with local currency prices from World Bank (2023), retrieving gross agricultural production at both local and international prices from FAO (2023), and converting population information to agricultural workers. The result is a measure of agricultural labor productivity.

Size of Agricultural Sector. The data on agricultural employment and value-added shares are from Gollin, Lagakos and Waugh (2014, Online Appendix Table 4).

Quantity and Quality of Education. We obtained the data on sectoral years of schooling from Gollin, Lagakos and Waugh (2014, Online Appendix Table 4). Since their measure of aggregate years of schooling does not, however, align with their reported agricultural employment share, we adjusted their sectoral years of schooling proportionally using their aggregate years of schooling and agricultural employment share. The data on return to education is directly taken from Schoellman (2012, Appendix A).

C Effects of Public and Private Education – An Example

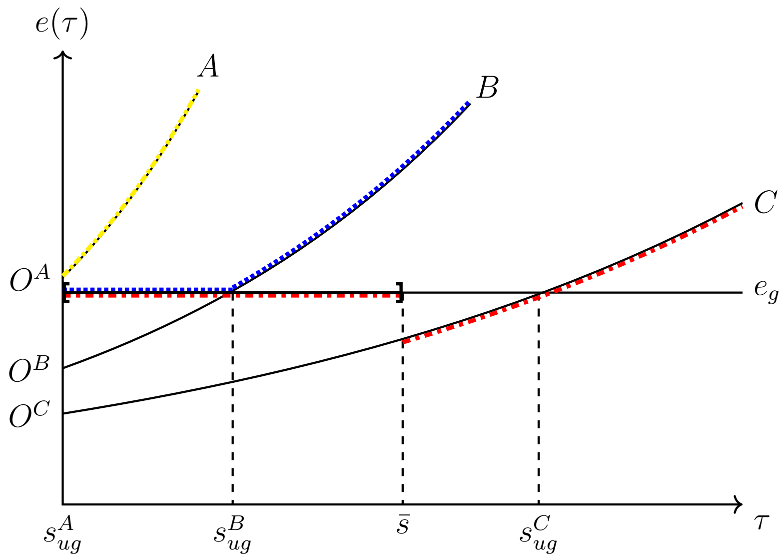

Figure C.2: Schematic Figure of Education Expenditure

In Figure C.2, three scenarios of education expenditures are presented. The figure illustrates the original schedules of purely private education investment, denoted by $\hat{e}(\tau)$, for three individuals A, B, and C, in the absence of a public education system. These schedules are represented by $O^A A$, $O^B B$, and $O^C C$, respectively. When a public education system $\{\bar{s}, e_g\}$ is introduced, the solution for $e(\tau)$ changes for individuals B and C, but not for individual A.[37] This is because individual A's $\hat{e}(\tau)$ is greater than e_g for all $\tau > 6$, indicating that one does not rely solely on public education expenditure at any age. Nonetheless, the introduction of the public education system still influences individual A's education expenditure. Specifically, A's private education investment expenditure is reduced to $\hat{e}^*(\tau) - e_g$.

[37]Note that the graphical representation does not account for the potential effects of the public education system on the years of schooling decision, s, and the individual's private education investment decision, $e_p(\tau)$. For the sake of clarity, however, we have simplified the graphical illustration by excluding these additional considerations.

The implementation of the public education system, in contrast, does affect individuals B and C. In the case of individual B, whose initial education investment schedule is denoted by $O^B B$, transitioning from private to public education during period $\tau \in [6, s_{ug}^B]$ would be advantageous, as the public education system would enhance B's human capital without incurring any private costs. Once individual B reaches the age of s_{ug}^B, she will begin allocating the portion of $\hat{e}^*(\tau)$ that exceeds e_g towards education. For individual C, a similar argument applies, with one notable difference: the public education subsidy ends at age $\bar{s}$, which is before s_{ug}^C. Consequently, individual C must rely entirely on her own funds for education investment during the period $\tau \in [\bar{s}, s]$.

D Steady State Equilibrium

Definition: A *steady state competitive equilibrium* involves sets of allocation $\{c_a(\tau), c_m(\tau), e_p(\tau)\}$ and $\{\kappa(s), h(s), s, D\}$ for each individual endowed with $x = (\psi, l, b\}$, a set of prices $\{p_a, p_m, w_i\}$, and government education policy $\{e_g, \overline{s}\}$ and tax rate ι, such that given prices, education policy, the tax rate, the stationary distribution of initial endowment $G(x)$ and the stationary age distribution of population $\Pi(\tau)$,

1. Individuals make decisions on $\{c_a(\tau), c_m(\tau), e_p(\tau)\}$ and $\{\kappa(s), h(s), s, D\}$ to maximize lifetime utility.
2. Wages are set equal to efficiency units of labor in each sector.
3. All goods markets and labor markets are cleared.
4. Government budget is balanced in each point of time.
5. The distribution of population with age τ and endowment x in each sector is stationary.

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