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Human capital composition and long-run economic growth

Mario F. Carillo [*,1]

Pompeu Fabra University, Department of Economics and Business, Barcelona School of Economics (BSE), Institute of Political Economy and Governance (IPEG), Barcelona, Spain

Centre for Studies in Economics and Finance (CSEF), University of Naples Federico II, Naples, Italy

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ABSTRACT

This study examines the impact of human capital composition on technological progress and its role in influencing the transition from stagnation to growth and the persistent income disparities across the globe. It posits that the trade-off between higher and lower education within an economy results in a trade-off between innovation and technology adoption. While highly educated individuals drive technological innovation, a workforce without adequate education can hinder technology adoption, thereby delaying the transition from stagnation to growth. Moreover, technology adoption complements technological progress especially in the modern era, when innovations are more challenging to adopt, thereby enhancing economic growth. This study provides empirical evidence to support the theoretical predictions. Overall, the findings form the basis for future studies on the critical role of human capital composition in economic development and offer novel insights for shaping education reforms at different stages of development.

1. Introduction

Throughout most of human history, societies worldwide had subsistence-level living standards and limited economic growth. However, over the past two centuries, various regions experienced a significant transition to an era of unprecedented improvement in living standards. Differences in the timing of the transition from pre-industrial stagnation to modern growth contributed significantly to the disparity in living standards that we observe across societies today (Galor, 2011). Understanding the timing of this transition is critical for understanding long-term development.

Several studies have highlighted the important role of human capital in explaining the transition from stagnation to growth. The interaction between technological progress and human capital influences investment in the quality of children (Galor and Weil, 1999, 2000; Carillo, 2021), life expectancy (Cervellati and Sunde, 2005), and the adoption of institutions that enhance growth (Doepke and Zilibotti, 2005). While the upper tail of the human capital distribution is a key factor of the innovation process that led to the Industrial Revolution (Mokyr, 2002, 2005; Jacob, 2014), various studies suggest that a sufficiently educated labor force was crucial for adopting innovations in the production process (Griliches, 1957; Nelson and Phelps, 1966; Benhabib and Spiegel, 2005b) and generally for economic growth (Becker et al., 2011; Madsen and Murtin, 2017). While studies have examined the impact of either the upper tail of the human capital distribution or mass education, their combined evolution and effects on the long-term economic trajectory are not fully understood. This understanding is important for shaping educational reform, as these initiatives may influence the composition of human capital beyond its average level, which has been widely underscored in existing literature (Gillman, 2021; Zeng and Zhang, 2022).

This study highlights this issue by hypothesizing that differences in the composition of human capital across societies and their impact on technology advancement and adoption contributed to the

* Correspondence to: Pompeu Fabra University, Department of Economics and Business, Barcelona School of Economics (BSE), Institute of Political Economy and Governance (IPEG), Barcelona, Spain.

E-mail address: mario.carillo@upf.edu.

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differential timing of the transition from pre-industrial stagnation to modern growth and long-term development. It hypothesizes that the human capital composition in an economy has two main implications for long-run growth. First, it involves a trade-off between technological innovation and adoption. Although highly educated individuals contribute to technological innovation, the lack of a large group of educated individuals among the working population delays technological adoption and the transition from stagnation to growth. Second, it involves a trade-off between the timing of the transition and long-run growth. Limited technology adoption prolonged the Malthusian stagnation, during which living standard improvements were primarily devoted to the number of children, spurring population growth over the long term. The resulting large population during the transition, and the associated large number of highly educated individuals fosters innovations, which in turn enhanced long-run economic growth and convergence to early-takeoff economies.

This study builds a model in which technology adoption serves two main purposes. First, it is necessary for innovation, which induces economic growth. A classic example is the precursor of the steam engine, developed by the Italian scholar Giambattista Della Porta, who used steam power to pump water in 1606. The first commercially successful engine did not appear until around 1712 (Brown, 2002, pp. 60). It was invented by Thomas Newcomen, paving the way for the Industrial Revolution (Stuart, 1829). However, his initial application was to pump water as well (Rolt, 1963). Thus, without the appropriate conditions for technology adoption, even the most powerful innovation in history may not trigger a technological breakthrough.

Second, adoption serves as a tool for storing, accessing, and transmitting knowledge, which can be improved over time. This mechanism was especially relevant in the pre-industrial ages, when a universal scientific language was yet to be developed, posing challenges in storing and accessing information. For example, the first scientific journal, the *Royal Society of London*, appeared in 1662 (Bekar and Lipsey, 2004). Only then were innovations stored and made accessible to the scientific community. Before that, they were passed down through generations primarily through their adoption, transforming them from theoretical projects into material "gadgets" (Ashton, 1955). These could be stored and understood despite the lack of a common scientific language. Further, they could be improved over generations (Bekar and Lipsey, 2004), guided by a process of "tinkering" (Mokyr, 1990), which laid the foundation for a basic mechanization based on experiments (Musson and Robinson, 1989). This indirect effect of adoption on technological advancement was mainly by artisans skilled in tinkering and producing gadgets, supplying a combination of intellectual and manual labor, thus comprising the mass in the middle of the human capital distribution.

The advanced model underscores this dual purpose of technological adoption and emphasizes the critical role of human capital composition in shaping long-term economic performance. By incorporating both elite education, fostering innovation, and mass education, facilitating adoption, the model yields two main results. First, the trade-off between the highly educated and those with intermediate-level education affects the timing of the demographic transition. While a greater number of innovators drive technological advancements, it is equally important to have a substantial number of people with the necessary education to adopt these innovations. Thus, the first result of the model emphasizes that a balance between these two components is crucial for expediting the transition process with this dual purpose of human capital – driving innovation and enabling adoption – serving as a catalyst for the transition to modern growth.

Second, the model demonstrates that the initial disadvantage resulting from an early emphasis on mass education and the resulting large proportion of individuals with intermediate levels of education is offset over time by the growing importance of technology adoption, particularly in the post-transition era. This finding suggests that despite possible delays in the transition process due to early mass education, the subsequent emphasis on technology adoption fosters growth and enables leapfrogging, resulting in accelerated economic development.

Both anecdotal and empirical evidence support these findings. For example, England and other Western societies, characterized by high prevalence of scientists and inventors, in addition to mass education, experienced early demographic transitions and sustained long-term growth. In addition to English innovators, Prussia's early mass education (Becker et al., 2011) and the educated French elites (Squicciarini and Voigtländer, 2015) demonstrate how Europe had the right composition of human capital to develop and adopt the technologies of the Industrial Revolution. Meanwhile, Latin American countries, characterized by wealthy elites who harnessed mass education (Sokoloff and Engerman, 2000), exhibited delayed industrialization and slack post-transition growth. Japan, despite achieving high levels of mass education early on Passin (1965), lagged behind in innovation compared to the US, Germany, and Britain for most of the 19th and 20th centuries (Nicholas, 2011). Its demographic transition began only in 1950 (Reher, 2004); eventually, Japan caught up in terms of economic growth and innovation (Nicholas, 2011). Although these examples support the hypotheses, this study empirically examines cross-country panel data, supporting the model's findings, and further highlights the importance of human capital composition for long-term development trajectories.

This study mainly contributes to four strands of the literature. First, it reconciles apparent discrepancies in findings related to persistence and reversals in global economic performance. Influential literature has emphasized that "deep-rooted" factors, such as geography and historical institutions, are important for explaining the differences in global living standards (Galor, 2005; Nunn, 2009; Spolaore and Wacziarg, 2013). However, while numerous studies have highlighted the persistence in economic development and technology adoption over thousands of years (Comin et al., 2010; Putterman and Weil, 2010; Chanda et al., 2014), others have emphasized reversals in the process of development (Acemoglu et al., 2002). This study enriches the existing literature by offering a novel mechanism that illustrates how historical factors may influence the distribution of human capital among the population, thereby partially explaining the patterns of persistence and reversals in long-term economic performances.

Second, this study connects the aforementioned comparative economic development literature with those emphasizing technology adoption as a by-product of specific skills and human capital levels. Several studies have hypothesized that human capital and technology are complementary (Griliches, 1957; Nelson and Phelps, 1966). This perspective gave rise to the emergence of several empirical studies in cross-country settings (Benhabib and Spiegel, 2005a) as well as across localities within countries (Foster and Rosenzweig, 1996; Carillo, 2021) indicating human capital accumulation as an essential precondition for technology adoption. By examining the relationship between human capital distribution, technology adoption, and the transition from stagnation to growth, this study bridges these two important strands of the literature.

Third, this study complements the literature by examining the interplay between human capital, population growth and fertility, and economic growth (Aghion and Howitt, 1992; Bucci and Prettner, 2020). Related to this influential stream of work, this study provides a tractable approach that introduces different levels of skill in elucidating the transition to modern growth within a unified growth theory framework (Galor, 2007). Thus, it extends the literature on factors that affect the long-term growth process, including the average level of human capital (Galor and Weil, 1999, 2000), life expectancy (Cervellati and Sunde, 2005), physical development (De La Croix and Licandro, 2013), fertility choices (Strulik and Weisdorf, 2008), and managerial practices (Carillo et al., 2019). Although this study draws from the seminal contribution of Galor and Mountford (2008), it differs substantially from it. The latter focuses on international trade and human capital formation and largely overlooks the causes and consequences of the within-country human capital distribution, which is the main focus of my study.

Fourth, by focusing on long-term economic performance, this study complements the recent literature on the importance of the distribution of human capital. For example, Trouvain (2022) emphasizes the innovation–adoption trade-off to explain development patterns from 1990 onward in developed economies, thus hypothesizing from the demographic trajectories emphasized in this study, which are typical of the earlier stages of development. Castelló and Doménech (2002) highlighted human capital inequality as a key measure of inequality across countries. Castelló-Climent and Mukhopadhyay (2013) showed that across Indian districts, a 1% increase in the number of citizens who have completed tertiary education contributed to a 13% increase in literacy rate. These findings highlight the importance of examining the human capital composition. However, these studies focus on its link with modern economic performance and largely ignore the transition from stagnation to growth from a long-term perspective, which is the focus of our study.

This study is presented as follows. Section 2 presents the theoretical model, which incorporates human capital composition in a long-run growth framework. Section 3 examines how human capital composition affects the timing of transition from the Malthusian stagnation and long-run growth. Section 4 provides empirical evidence to support the hypotheses of the model. Section 5 concludes.

2. The model

This section introduces a long-run growth model that includes the endogenous transition from Malthusian stagnation to the modern growth regime. Consider an overlapping generation model that evolves over infinite discrete time. For each period t, a finite homogeneous good, Y_t, can be produced according to two alternative regimes of production, called the *old regime* and the *new regime*. For tractability, the distribution of human capital in the population is represented by three levels of skills.[2] These three levels of skills correspond to three sources of labor, which are the factors of production.[3] The three sources of labor are manual labor, human capital-intensive labor, and a combination of the two.

Manual labor, L_t, is the amount of labor provided by unskilled individuals. High-skilled labor, H_t, is the amount of labor provided by the highly educated labor force, who have a comparative advantage in innovating and are thus called *innovators*. A third source of labor force, representing the middle of the human capital distribution, is the combination of manual and intellectual labor, M_t, which is supplied by individuals who are sufficiently educated to understand and adopt innovations. Owing to their comparative advantage in adopting innovations, they are called *adopters*.

2.1. Production

Production can occur under two alternative production regimes, the *old regime* and *new regime*.

2.1.1. The old regime

During early stages of technological development, new inventions, mainly produced by high-skilled workers, could be directly implemented by the manual labor force. When knowledge levels are low, innovations are easily adopted because an understanding of how they function practically can be understood by unskilled individuals. Even if the masses did not understand the theoretical foundation, the simplicity of early technology is reflected in the simplicity of its adoption, implying that no special forms of education or skills are required to implement them in production.

Ley farming is an example of such technologies, which is an agricultural system where land is alternately seeded for grain and left fallow. During the fallow period, the soil is enriched with roots of grasses and other plants. While sophisticated chemical skills were needed to invent ley farming, which was introduced in an advanced form at the beginning of the 17th century (Stapledon et al., 1948), farmers could easily understand and adopt this method. They only needed to know which types of grass should be cultivated during the fallow period to increase yields.

Given the anecdotal evidence, the *old regime* of production included only manual and highly educated labor.[4]

$$Y_t^o = A_t^o H_t^\alpha L_t^{1-\alpha} = A_t^o L_t h_t^\alpha \tag{1}$$

where h_t is the proportion of skilled over unskilled labor, which is given by $h_t \equiv \frac{H_t}{L_t}$.

Highly educated individuals are modeled as directly contributing to production through creating innovations. Moreover, they indirectly contribute to knowledge accumulation, as discussed in Section 2.3. Thus, during the early stages of technological development, there was a need for human capital to innovate but not adopt. However, the limited understanding of new techniques by manual laborers may have hindered the improvement of these newly adopted techniques. This additional factor will be discussed in Section 2.3.

2.1.2. The new regime

When the technology is increasingly complex, innovations are mainly adopted by educated individuals who can understand and implement them in the production process. This holds for most advanced technical innovations that require skills to comprehend and adopt them. Artisans and craftsmen, for example, were specifically trained for using and creating gadgets. This source of labor, representing a combination of manual and intellectual labor, formed the mass in the middle of the human capital distribution.[5]

Production in the *new regime* occurs based on a production function that includes labor by manual workers, innovators, and adopters.

$$Y_t^n = A_t^n H_t^\beta M_t^\phi L_t^{1-\beta-\phi} = A_t^n L_t h_t^\beta m_t^\phi \tag{2}$$

where m_t is the proportion of adopters over manual labor force, $m_t \equiv \frac{M_t}{L_t}$ and $h_t \equiv \frac{H_t}{L_t}$

2.1.3. Factor prices

Markets are perfectly competitive. The inverse demands for production factors depend on the regime employed. The inverse demand for highly skilled labor, given (1) and (2),

$$w_t^h = \begin{cases} \alpha A_t^o h_t^{\alpha-1} & \text{if } Y_t^o > 0 \\ \beta A_t^n h_t^{\beta-1} m_t^\phi & \text{if } Y_t^n > 0 \end{cases} \tag{3}$$

[2] The use of a discrete distribution is consistent with the indivisibility of skills and degrees.

[3] If land were also considered as a constant factor of production with no property rights, as in Galor and Moav (2002), the results would remain qualitatively unchanged. Further, if capital were considered as a factor of production, the model would become extremely complex to solve. For a growth model that considers both physical and human capital, see e.g. Bond et al. (1996).

[4] Appendix P presents an extension with an intermediate sector in which innovators produce innovations, constituting an input of the production of the final homogeneous good. I show that the model containing this extension is isomorphic to the one presented in the main text.

[5] For recent evidence of the increase in the number of skilled workers in the English Industrial Revolution, see De Pleijt et al. (2020).

where w_t^h is the wage of innovators. The inverse demand for manual labor, given (1) and (2), is

$$w_t^l = \begin{cases} (1-\alpha)A_t^o h_t^\alpha & \text{if } Y_t^o > 0 \\ (1-\beta-\phi)A_t^n h_t^\beta m_t^\phi & \text{if } Y_t^n > 0 \end{cases} \tag{4}$$

where w_t^l is the wage of unskilled labor. The inverse demand for adopters' labor, given (2), is

$$w_t^m = \phi A_t^n h_t^\beta m_t^{\phi-1} \quad \text{if } Y_t^n > 0 \tag{5}$$

where w_t^m is the wage of adopters, which will be employed only in the new regime. Moreover, given (3) and (4), the wage ratio of the innovators over manual labor is

$$\frac{w_t^h}{w_t^l} = \begin{cases} \frac{\alpha}{1-\alpha}\frac{1}{h_t} & \equiv \omega^h\left(h_t^o\right) \quad \text{if } Y_t^o > 0 \\ \left(\frac{\beta}{1-\beta-\phi}\right)\frac{1}{h_t} & \equiv \omega^h\left(h_t^n\right) \quad \text{if } Y_t^n > 0 \end{cases} \tag{6}$$

Given (5) and (4) the wage ratio of the adopters to manual labor is given by

$$\frac{w_t^m}{w_t^l} = \left(\frac{\phi}{1-\beta-\phi}\right)\frac{1}{m_t} \equiv \omega^m\left(m_t\right) \text{ if } Y_t^n > 0 \tag{7}$$

From the properties of the production functions, it follows that the following properties characterize wage ratios:

$\omega'(j_t) < 0$, $\lim_{j_t\to 0}\omega^j(j_t) \to \infty$, $\lim_{j_t\to\infty}\omega^j(j_t) \to 0$ with $j = m, h$ and $\forall j_t \in \left[0, \infty\right)$.

2.2. The individual choice

Individuals live for two periods of time: childhood and parenthood. During their childhood, they consume a fraction of their parents' endowment, which consists of one unit of time. All decisions are made in adulthood. Parents are endowed with one unit of time as manual labor, l; adopters labor, m; or innovators labor, h, depending on the level of education they received in childhood. They distribute their endowment between childrearing and consumption.

2.2.1. Preferences and budget constraints

Preferences are determined by parental consumption and the potential aggregate income of their children (Galor and Mountford, 2008). Parents i, where $i = l, m, h$, choose the number of children $n^{i,j}$ for each level of education j, with $j = l, m, h$, and parental utility from each child depends on the wage they earn on the market. In other words, parents get their utility according to the utility function

$$u_t^i = (1-\gamma)lnc_t^i + \gamma ln\left(w_{t+1}^l n_t^{i,l} + w_{t+1}^m n_t^{i,m} + w_{t+1}^h n_t^{i,h}\right)$$

where c_t^i is the parental consumption at time t, $n_t^{i,j}$ is the number of children of type j reared by parent i at time t.[6]

The budget constraint is given by

$$c_t^i + w_t^i\left(n_t^{i,l}\tau^l + n_t^{i,m}\tau^m + n_t^{i,h}\tau^h\right) \le w_t^i \tag{8}$$

where τ^j is the cost of having a child of type j with $j = l, m, h$ and $\tau^l < \tau^m < \tau^h$. Therefore, it is assumed that the more educated the offspring is, the higher the cost of raising a child at that level of education will be.[7]

[6] Note that, as mortality is not explicitly modeled, n_t can be interpreted as the number of surviving children.

[7] Alternatively, one may contend that although artisans are less educated than philosophers or mathematicians, the scarcity of certain skills, such as carpenter or armorer ones, involves difficulties in procurement, resulting in higher costs. However, most artisans' acquire skills through job training or, in more advanced stages of urbanization, through apprenticeship under the supervision of masters. Both these approaches to acquiring this source of human capital are characterized by a higher degree of economies of scale in terms of the acquisition of high-level human capital, thereby implying a lower cost than other forms of human capital.

The subsistence constraint is given by

$$c_t^i \ge \tilde{c} \tag{9}$$

where $\tilde{c}$ is the subsistence level of consumption.[8]

2.2.2. Optimization

The optimization problem, detailed in Appendix A, shows that the optimal share of innovators and of adopters are unique and constant in both regimes. In the following, I explain these arguments.

Lemma 1. *Consider the old regime of production. There exists a unique ratio of innovators to manual labor ratio, $(h^o)^*$ such that*

$$\frac{w_t^{o,h}}{w_t^{o,l}} = \omega^j((h^o)^*) = \frac{\tau^h}{\tau^l} \tag{10}$$

where,

$n_t^{i,l} = 0$ if $h_t < (h_t^o)^*$
$n_t^{i,h} = 0$ if $h_t > (h_t^o)^*$

Proof. The uniqueness of $(h_t^o)^*$ follows from the properties of $\omega((h_t^o)^*)$, which is monotonically decreasing in its argument, noting that $\tau^h/\tau^l > 0$. The remaining part is a corollary of (A.5). □

Hence, during the old regime, if $h_t < (h_t^o)^*$, the relative reward for having an uneducated offspring is lower than the relative cost; thus, there are no incentives for raising uneducated offspring, suggesting an increase in h_t. In contrast, if $h_t > (h_t^o)^*$, there are no incentives for raising high-human-capital offspring, implying a decrease in h_t up to $(h_t^o)^*$. The following proposition validates this explanation.

Proposition 1. *If the old regime of production is employed then $h_t = (h_t^o)^*$, that is, $h_t = (h_t^o)^*$ if $Y_t^o > 0$ and therefore wages of the innovators are*

$$w_t^h = \alpha A_t^o\left[(h_t^o)^*\right]^{\alpha-1} \quad \text{if } Y_t^o > 0 \tag{11}$$

wages of the manual workers are

$$w_t^l = (1-\alpha)A_t^o\left[(h_t^o)^*\right]^{\alpha} \quad \text{if } Y_t^o > 0 \tag{12}$$

and thus

$$(h_t^o)^* = \left(\frac{\alpha}{1-\alpha}\right)\frac{\tau^l}{\tau^h} \tag{13}$$

where the latter comes from (6), given Lemma 1.

Proof. Suppose not, then there exists $\tilde{h}_t$, which is a level of h_t that satisfies optimization condition (A.5) and such that $\tilde{h}_t > (h_t^o)^*$ and $Y_t^o > 0$. However, $\tilde{h}_t > (h_t^o)^*$ implies that $w_t^h/w_t^l < \tau^h/\tau^l$, then (A.5) implies that $n_{t-1}^{i,h} = 0$, then $H_t = 0$ and $Y_t^o = 0$, which yields a contradiction. Similarly, if $\tilde{h}_t < (h_t^o)^*$, then $L_t = 0$ and $Y_t^o = 0$. □

As mentioned, Eq. (13) shows that during the old regime, the optimal proportion of innovators versus manual labor force is constant over time; that is

$$(h_t^o)^* = (h^o)^* \; \forall t$$

Lemma 2. *Considering the new regime, there exists a unique innovators to manual labor ratio, $(h^n)^*$, and a unique adopters to manual labor ratio, m^*, such that*

$$\frac{w_t^{n,h}}{w_t^{n,l}} = \omega^j((h_t^n)^*) = \frac{\tau^h}{\tau^l} \tag{14}$$

[8] An alternative modeling choice could be based on Stone–Geary preferences, as in e.g. Nakamura (2018). However, such a design in a Unified Growth Theory framework complicates the model to the point of intractability.

$$\frac{w_t^m}{w_t^{n,l}} = \omega^m(m_t^*) = \frac{\tau^m}{\tau^l} \tag{15}$$

where,

$$\begin{aligned} n_t^{i,h} &= 0 \quad \text{if } h_t > (h^n)^* \quad \text{or if } h_t = (h^n)^* \quad \text{and } m_t < m_t^* \\ n_t^{i,m} &= 0 \quad \text{if } m_t > m_t^* \quad \text{or if } m_t = m_t^* \quad \text{and } h_t < h_t^* \\ n_t^{i,l} &= 0 \quad \text{if } h_t < (h^n)^* \quad \text{or } m_t < m_t^* \end{aligned}$$

Proof. The uniqueness of $(h_t^n)^*$ and m_t^* follows from the properties of $\omega^h((h_t^n)^*)$ and $\omega^m(m_t^*)$, which are monotonically decreasing in their arguments, noting that $\tau^h/\tau^l > 0$ and $\tau^m/\tau^l > 0$. The remaining part is a corollary of (A.6). □

Hence, during the new regime, if $h_t > (h_t^n)^*$ there are no incentives to raise highly educated children, implying a reduction in h_t. In the case where $h_t < (h_t^n)^*$, there are no incentives to raise uneducated children because the relative reward of raising highly educated offspring is higher; therefore, resources flow in this direction, thereby increasing h_t. The same logic applies to m_t. Thus, if the proportion of one of the three sources of the labor force is lower than optimal, the potential relative wage of that child is higher than the relative cost, encouraging parents to invest their resources in rearing offspring with that particular level of education, ultimately increasing their relative proportion and reducing their relative wage until Eqs. (14) and (15) are satisfied. The following proposition validates this explanation.

Proposition 2. *If the new regime of production is used, then $h_t = (h_t^n)^*$ and $m_t = m_t^*$; that is $h_t = (h_t^n)^*$ and $m_t = m_t^*$ if $Y_t^n > 0$ and, therefore, the innovators' wages are*

$$w_t^h = \beta A_t^n \left[(h^n)^*\right]^{\beta-1} \left[m^*\right]^{\phi} \text{ if } Y_t^n > 0$$

the adopters' wages are

$$w_t^m = \phi A_t^n \left[(h^n)^*\right]^{\beta} \left[m^*\right]^{\phi-1} \text{ if } Y_t^n > 0$$

the manual workers' wages are

$$w_t^l = (1-\beta-\phi) A_t^n \left[(h^n)^*\right]^{\beta} \left[m^*\right]^{\phi} \quad \text{if } Y_t^n > 0 \tag{16}$$

and, thus

$$(h_t^n)^* = \left(\frac{\beta}{1-\beta-\phi}\right)\frac{\tau^l}{\tau^h} \tag{17}$$

$$m_t^* = \left(\frac{\phi}{1-\beta-\phi}\right)\frac{\tau^l}{\tau^m} \tag{18}$$

where (17) and (18) are obtained from (6) and (7), given Lemma 2.

Proof. Suppose not, then there exists $\tilde{h}_t$, which is a level of h_t that satisfies optimization condition (A.6) and such that $\tilde{h}_t > (h_t^n)^*$ and $Y_t^n > 0$. However, $\tilde{h}_t > (h_t^n)^*$ implies that $w_t^h/w_t^l < \tau^h/\tau^l$, then (A.6) implies that $n_{t-1}^{i,h} = 0$, then $H_t = 0$ and $Y_t^n = 0$, which is a contradiction. Similarly, if $\tilde{h}_t < (h_t^o)^*$, then $L_t = 0$ and $Y_t^n = 0$. Similarly, if $\tilde{m}_t < m_t^*$, then $M_t = 0$ and $Y_t^n = 0$. Or, if $\tilde{m}_t > m_t^*$, then $L_t = 0$ and $Y_t^n = 0$. □

Observe from (17) and (18) that during the new regime, the optimal ratios of innovators to manual labor and adopters to manual labor are constant over time, that is

$$(h_t^n)^* = (h^n)^* \text{ and } m_t^* = m^*;\ \forall t \tag{19}$$

Furthermore, from (10) and (14),

$$\omega^h((h^o)^*) = \omega^h((h^n)^*) \tag{20}$$

implying that

$$\left(\frac{\alpha}{1-\alpha}\right)(h^n)^* = \left(\frac{\beta}{1-\beta-\phi}\right)(h^o)^*$$

Under the plausible assumption that production in the old regime is relatively more manual-labor-intensive compared with the new regime ($\alpha/(1-\alpha) < \beta/(1-\beta-\phi)$), the prevalence of innovators compared with manual labor force is higher in the new regime; that is $(h^n)^* > (h^o)^*$.

2.3. Technological progress

During the initial stages of development, inventors generated ideas and projects through rudimentary R&D. This process led to innovations that not only served as input in production but also positively externalities on the advancements in the technological frontier.

Therefore, technological progress is modeled to positively depend on the number of innovators in the economy. In other words, in the old regime, technology development between time t and $t+1$ depends on the number of innovators in the economy at time t:

$$\frac{A_{t+1}^o - A_t^o}{A_t^o} = \Omega(H_t) \tag{21}$$

where A_0^o is historically given and the innovation function $\Omega(H_t)$ is an increasing and concave function $\Omega' > 0$ and $\Omega'' < 0$ and $\Omega \in (0,\infty)$.

During the new regime of production, in addition to the effect of innovators, the presence of a labor force that can adopt innovations and improve them over time is an additional source of technological accumulation

$$\frac{A_{t+1}^n - A_t^n}{A_t^n} = \Omega(H_t)\ \left(1 + \lambda(M_t/N_t)\right) \tag{22}$$

where A_0^n is historically given and the adoption rate $\lambda' > 0$, $\lambda'' < 0$ and $\lambda \in (0,\infty)$ with $\lambda(0) > 0$. The adoption rate λ depends on the fraction of adopters in the economy, $\frac{M_t}{N_t}$; the higher the fraction of adopters, the closer the economy is to perfect adoption. As $\lambda(0) > 0$, technological progress is faster in the new regime.

2.4. Viability of production regimes

The two regimes are available at any point in time and agents choose the preferred regime based on the regime-specific wage they earn. In other words,

$$\text{every agent } i \text{ chooses the regime } j \text{ if } w_t^{j,i} \geq w_t^{-j,i} \forall i = l, m, h; \forall t \tag{23}$$

The framework implies that only one regime of production is in effect at any given time (see Appendix F for proof). In other words, each agent chooses the preferred regime based on the reward that can be earned. Propositions 1 and 2 suggest that a regime determines the proportions of production factors in the economy as a positive and finite constant (see Eqs. (13), (17), and (18)). Thus, factor prices cannot equalize across regimes, preventing the coexistence of these two modes of production. Meanwhile, regime-specific wages are given (although not constant, as they depend on the level of technology A_t^j for $j = old, new$). At any time, agents compare these wages to determine the operative regime. Moreover, the optimal skill ratios depend solely on relative wages independent of parental types. Thus, parents shift to the new regime and choose the optimal skill ratio for their children, which is the same across types.

As the wage ratios remain constant over time, if the new regime is economically viable for the manual laborers, it will be feasible for all other agents in the economy (see Appendix G for a proof). Under the old regime, those who adopt the system are not rewarded; thus, parents will invest in the other types. Investment in the intermediate level of education will be economically viable when the new regime is operative, that is, only when both the innovators and adopters find the new regime beneficial. The difference between what manual workers can earn in the new regime versus the old regime is the threshold rule for shifting to the new regime of production.

2.5. The time path of the economy

2.5.1. Technological progress

The productivity parameters are restricted such that the new regime is not economically viable at time zero; that is[9]

$$\frac{A_0^o}{A_0^n} > \frac{1-\beta-\phi}{1-\alpha} \cdot \frac{\left[\left(\frac{\beta}{1-\beta-\phi}\right)\frac{\tau^l}{\tau^h}\right]^\beta \left[\left(\frac{\phi}{1-\beta-\phi}\right)\frac{\tau^l}{\tau^m}\right]^\phi}{\left[\left(\frac{\alpha}{1-\alpha}\right)\frac{\tau^l}{\tau^h}\right]^\alpha} \tag{24}$$

During the old regime, knowledge advancement increased the potential productivity of the new regime over time. The underlying idea is that a latent technological advancement exists. Through a process of tinkering and learning in laboratories, unlike on-the-job learning, workers acquire the necessary skills for the adoption process, leading to rapid improvement in the latent technological advancement, which ultimately makes the new regime viable. This is technically ensured by Eq. (22), stipulating that even if there are no adopters, the adoption rate remains positive (i.e., $\lambda(0) > 0$).

As there is rapid latent technological advancement in the new regime than in the old regime, and since the sole source of time-varying wages is total productivity growth, there is a specific point in time, denoted as t^*, at which the new regime yields higher wages than the old regime. This leads to the transition to the new regime (for proof, refer to Appendix H). Furthermore, this implies that, regardless of the economy's position in the h_t, m_t plane (as illustrated in Fig. 1), it will eventually experience a transition from stagnation to growth (for a proof, see Appendix I).

The new production regime requires a sufficiently advanced level of knowledge to assemble skilled labor force. This can possibly be achieved when the subsistence constraint is no longer binding. Consequently, it can be hypothesized that in the new regime as well, the subsistence constraint is no longer binding. To simplify the analysis, I assume that the escape from stagnation coincides with the transition to the new production regime, which can be expressed as

$$t^* = t^c \tag{25}$$

which is equivalent to assuming that the wage level w_{t^*}, where $w_{t^*} \equiv w_t^{n,l} = w_t^{o,l}$, equals $w_{t^*} = \tilde{c}/(1-\gamma)$. Although this assumption simplifies the analysis, it does not affect the results of this study.[10]

2.5.2. Timing of the transition

Given the quantities h^*; m^* and the threshold G_t, it is possible to determine the time at which an economy will experience the transition to the new regime, t^*, where G_t is such that (G.14) is satisfied with equality, that is,

$$G_t = \left\{G(h_t, m_t) | w_t^{n,l} - w_t^{o,l} = 0\right\} \ \forall t \le t^* \text{ where } h_t \equiv h_t^n.$$

Before the transition takes place, only the old regime is operative (see condition (24)). Furthermore, the threshold G_t, $\forall t < t^*$, represents the set of points (h_t, m_t), where $h_t^n \equiv h_t$, such that the new regime is viable, which is a function of the proportions of the factors of production and the parameters of the model (for a more formal definition, see Appendix J). It can be represented on an h_t, m_t plane (see Fig. 1), and the new regime is viable when the proportions (h^*, m^*) satisfy the threshold rule G_t.

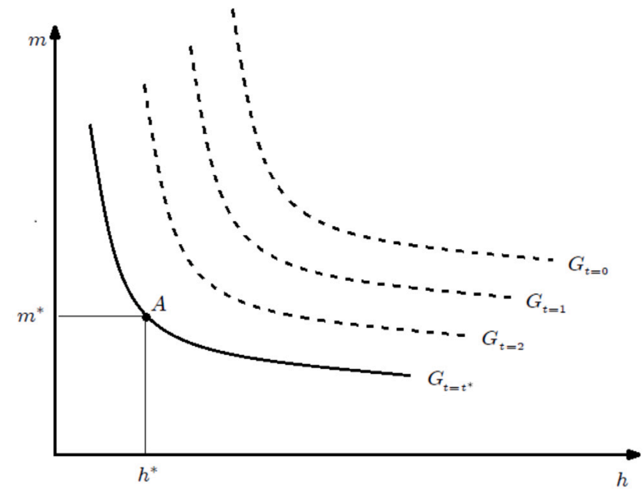


Fig. 1. Timing of the transition.
Notes: At t^*, economy A experiences the transition from the old to the new regime.

The timing of the transition can be measured considering the time that elapsed between $t = 0$ and the time in which the optimal proportions of the factors of production belong to the threshold, $t^* | (h^*, m^*) \in G_t^*$. Fig. 1 shows the movement of the threshold, G_t, until the transition phase (i.e., $t \le t^*$). Therefore, the timing of the transition, t^*, is a function of the distance from the point (h^*, m^*) and the curve $G_{t=0}$. Specifically, time is given by the ratio between distance and speed; thus, the timing of the transition from stagnation to growth is given as follows:

$$t^* = \frac{d^*}{s_{t^*}}$$

where d^* is the minimum distance between (h^*, m^*) and $G_{t=0}$, and s_{t^*} is the speed of convergence to the new regime.[11] Therefore, observing (13), (17), and (18), the time of the transition can be expressed as

$$t^* = t(\tau^l, \tau^m, \tau^h; \xi)$$

where $\xi \equiv \xi(\alpha, \beta, \phi, A_0^o, A_0^n, \lambda(0))$.

The costs of raising offspring, τ^j, with $j = l, m, h$, affects the human capital composition in the economy. Changes in these costs imply changes in the shares of innovators and adopters in the economy, which influence the economic viability of the new regime and the timing of the transition from stagnation to growth.

2.5.3. Timing of the model

The timing of the model is as follows. Initially, considering the low level of technology (i.e., $\alpha A_0^o[(h^o)^*]^\alpha(1-\gamma) < \tilde{c}$), the subsistence constraint is binding for the innovators and manual workers. Therefore, the initial stage of the model shows all features of the Malthusian stagnation, in which improvements in technological progress are eroded by population growth and do not translate into increases in long-term living standards. Over time, considering condition (24), production occurs under the old regime with the equilibrium proportion of factors. Factor prices are determined by Proposition 1 and the new regime is not economically viable.

Given (25) and Lemmas H and I, the escape from subsistence is associated with the transition to the new regime of production. Thus, the transition to this second stage includes all features of the demographic transition—a period in which the decreased fertility is associated with investment in mass education, which is rewarded in the new regime. During this modern stage of development, the model

[9] The equation is derived from the condition such that the wage at time zero of unskilled workers is lower in the new regime (specified in Proposition 2) than in the old regime (specified in Proposition 1).

[10] Alternatively, one may assume that $t^c < t^*$. This would complicate the analysis without changing the results. Furthermore, it is unclear whether the escape from the Malthusian anticipated the transition to a modern mode of production. For example, while in France, the demographic transition occurred before the Industrial Revolution, in Italy it began in the late 19th century, thus after the first wave of industrialization (Delventhal et al., 2021; Reher, 2004; Zamagni, 1993).

[11] See Appendix for the functional form of d^* and s_{t^*}

demonstrates production in the new regime, and the equilibrium ratio of proportion factors and prices is determined by Proposition 2.

3. Comparative statics

Environmental and institutional differences may affect the costs of raising children and influence human capital composition and the long-term evolution of economic performance. This section explores how the changes in the model parameters influence the transition to modern growth and the economy's growth rate.[12] In Section 4, I offer empirical evidence to support these predictions and suggest possible methods for finding exogenous variation for future in-depth empirical studies.

Main findings.

- An increase in the cost of raising adopters (τ^m) results in a low prevalence of adopters, leading to a delayed transition and slower post-transition growth in output *per capita*.
- An increase in the cost of raising highly educated children (τ^h) leads to fewer innovators in the economy, which in turn causes a lag in transition. However, this situation leads to a large number of individuals with intermediate-level education, which promotes long-term growth in output *per capita*.

3.1. Timing of the transition

Each point in the h, m plane, as shown in Fig. 2, represents a potential post-transition human capital composition, depending on the cost parameters. The distance from this point to the threshold $G_{t=0}$ is directly proportional to the timing of the transition from stagnation to growth. Differences in costs associated with raising children with different levels of education—τ^l, τ^m, and τ^h—result in changes in the human capital composition and the transition timing, t^*.[13] The following section provides a graphical representation of the comparative statics related to the timing of the transition. For a more detailed mathematical analysis, see Appendix D.

Fig. 2 shows that increased cost related to raising highly educated children, denoted as τ^h, can reduce the prevalence of innovators, leading to a shift from point A to point B. This change results in a greater distance between points AA' and BB'. Thus, economy B would have a delayed transition than economy A. A high cost associated with raising adopters, denoted as τ^m, lowers the number of adopters and shifts the economy from point A to point C, thus delaying the transition (i.e., $CC' > AA'$). Finally, the high cost of raising uneducated offspring, represented as τ^l, leads to a higher prevalence of innovators and adopters, accelerating the process of technological progress and resulting in an earlier take-off.

The model predicts that during the initial phases of development, the human capital composition included a trade-off between innovation and adoption, significantly affecting the timing of the transition from stagnation to growth. The next section examines the impact of human capital composition on economic growth following the escape from Malthusian stagnation.

[12] This comparison is based on the assumption that the economies under analysis operate in isolation from a technological perspective. This assumption resonates with the observation of imperfect technology transmission among societies, particularly during the early stages of development. In line with the theoretical framework, technologies primarily diffused when innovations were incorporated into the production process, involving the creation of devices that could be disseminated both across geographical distances and through time. For a model encompassing open economies, see e.g. Galor and Mountford (2008).

[13] Notably variations in τ^j (where $j = l, m, h$) have a greater impact on the distance function, thereby influencing the timing of the transition. Therefore, analyzing the effect of the distance is sufficient to understand the overall impact on the timing of the transition.

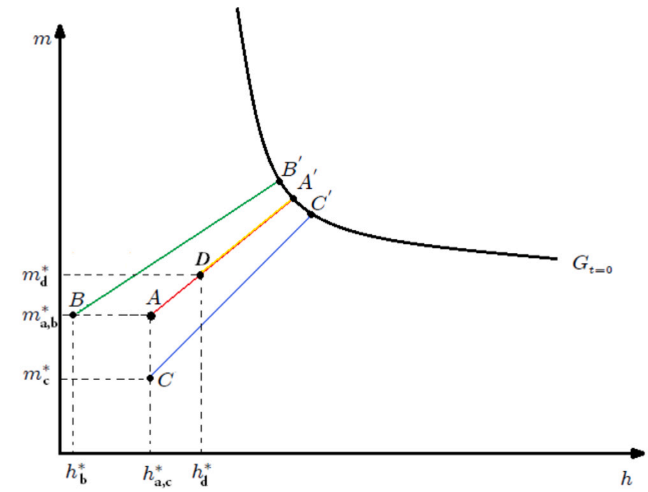


Fig. 2. Human capital composition and the timing of the transition.
Notes: *Case 1* [$\tau^l_d > \tau^l_a$] - In country D, the proportion of unskilled workers is lower than in A; *Case 2* [$\tau^h_b > \tau^h_a$] - In country B the proportion of adopters is lower than in A; *Case 3* [$\tau^m_c > \tau^m_a$] - In country C the proportion of adopters is higher than in A.

3.2. Post-transition economic growth

During the pre-industrial stages of development, potential improvements in living standards were eroded by proportional population growth. Consistent with this feature of the Malthusian stagnation, the model demonstrates that increases in parental income led to higher fertility rates, resulting in limited improvements in living standards. Consequently, growth in output *per capita* is zero during the old regime, when the Malthusian constraint is binding. The departure from the Malthusian trap is associated with the transition to a modern growth regime, leading to significant increases in output *per capita* and positive economic growth. Therefore, as shown in Appendix K, the growth rate of output in the two regimes is given by,[14]

$$g^o_y = 0, \forall t < t^*$$

$$g^n_y = \Omega(H_t)\ \left(1 + \lambda(M_t/N_t)\right), \forall t \geq t^* \tag{26}$$

. where the latter can be rewritten as

$$g^n_y = \Omega(n^{t-t^*})\chi\ (1 + \lambda(M_t/N_t)), \forall t \geq t^* \tag{27}$$

Eq. (27) establishes the link between human capital composition and the growth rate of output *per capita*. The results are shown in Fig. 3.

In the first scenario, economy D has a higher cost of raising uneducated offspring than A, i.e., $\tau^l_d > \tau^l_a$. Thus, in economy D, more educated children will be raised, leading to a higher level of human capital in the economy and an earlier transition, as shown in Fig. 3. However, an increase in τ^l leads to a smaller population during the transition, ultimately leading to lower long-term growth in output *per capita* (Fig. 3, case 1).

The second case examines the effect of an increase in the cost of raising highly educated children, denoted as τ^h, leading to fewer innovators in B than in A (Fig. 2) and a delayed transition. However, this delay is offset by faster long-term growth (Fig. 3, case 2). Fewer innovators (indicated by high τ^h) result in prolonged Malthusian mechanism, thereby leading to a higher population once the transition occurs. The substantial *number* of innovators (due to large population),

[14] Where $g^j_y = \frac{Y^j_{t+1}/N^j_{t+1} - Y^j_t/N^j_t}{Y^j_t/N^j_t}$ and $j = old, new$.

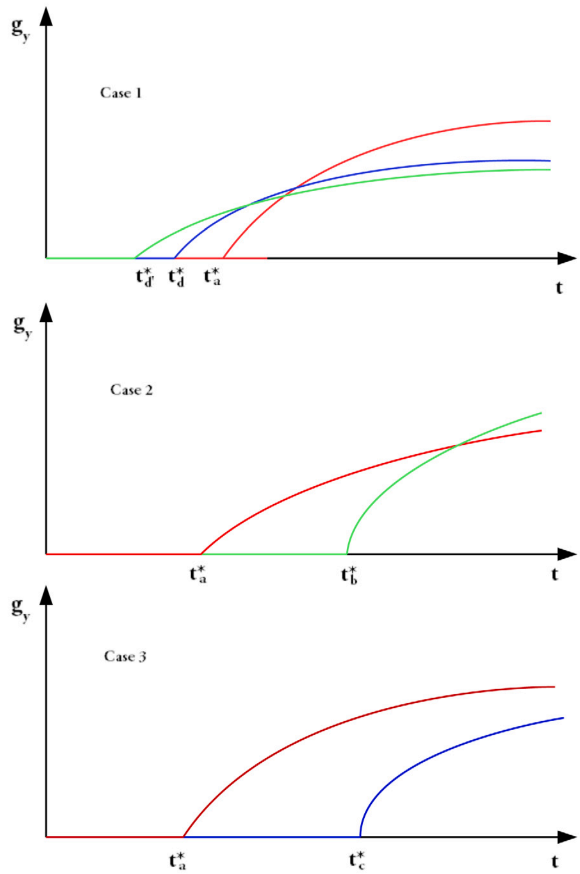


Fig. 3. Human capital composition and post-transition growth.
Notes: *Case 1* $[\tau^l_{d'} > \tau^l_d > \tau^l_a]$ - In country D, the level of human capital is higher than in Country A; *Case 2* $[\tau^h_b > \tau^h_a]$ - Country B shows fewer innovators than Country A; *Case 3* $[\tau^m_c > \tau^m_a]$ - Country C shows fewer adopters than Country A.

supported by a larger *fraction* of the adopters, ultimately leads to higher post-Malthusian growth. Consequently, in this case, the model predicts a reversal of fortunes; the initial disadvantage in the transition timing due to fewer inventors is offset by an advantage in the long-term growth rate following the transition.[15]

In the last scenario, the cost of raising sufficiently educated offspring to contribute to technology formation by adopting innovations in the production process, τ^m, is higher in economy C than in A (Fig. 2). Economy C shows a low prevalence of adopters and a lag in transition, resulting in slower post-transition growth (Fig. 3, case 3).

4. Empirical evidence

This section examines the variation across countries and over time to empirically support the three main hypotheses of the model.[16] First, human capital composition is linked to the demographic transition and its timing. Second, countries with a lagged transition had a larger population during the transition. Third, human capital composition influenced economic growth after the transition. I further examine whether the evidence supports these hypotheses. I then show the possible methods for examining exogenous variation for future in-depth empirical studies.

This empirical analysis examines education inequality as a measure of human capital composition and links it to the timing of the demographic transition and growth in income *per capita*. Finding an objective measure of the transition to modern growth is difficult. However, considering the hypothesized link with the demographic transition, the empirical analysis employs the timing of demographic transition as a proxy, developed by Reher (2004), consistent with recent literature (e.g., Dalgaard et al. (2021)). This measure provides the estimates of the year of the fertility transition as the beginning of the first 5-year period, when fertility declined by at least 8% over the two 5-year periods (Reher, 2004). The available measure of education inequality is the Gini index of education, ranging from 0 (perfect equality) to 100 (perfect inequality). Given that education is bounded above, and controlling for average education, a high Gini proxies for the low prevalence of adopters.

Fig. 4 shows the scatter plots illustrating the relationship between the year of the demographic transition and the inequality of education, measured by the Gini index, in the five years preceding the demographic transition (top panel). It also shows the relationship between the year of the demographic transition and the natural logarithm of population density (bottom panel). The axes of Fig. 4 are normalized to zero because the variables used in the regressions have been centered by subtracting their mean and scaled by dividing by their standard deviation. The average year of demographic transition is 1966. The underlying regression controls for agricultural suitability and geographical region-fixed effects. Moreover, the regression in the top panel controls for the average education level in the five years before the transition.

The scatter plot in the top panel of Fig. 4 demonstrates a positive and statistically significant correlation between the year of the demographic transition and the Gini index of education. This finding is consistent with the theoretical framework, indicating that the composition of human capital – beyond the mere average – is key to the demographic transition. A higher Gini index of education, indicative of fewer adopters, supports the delayed demographic transition, consistent with the prediction of the theoretical model, as shown in Fig. 2, Case 2.

The scatter plot in the bottom panel of Fig. 4 indicates a positive and statistically significant correlation between the year of the demographic transition and population density during transition. This observation supports the theoretical proposition that a delayed demographic transition and the associated prolonged Malthusian demographic pressures led to a larger population size at the onset of the transition.

Furthermore, I examine the relationship between human capital composition and post-transition economic growth. I therefore use the following econometric specification:

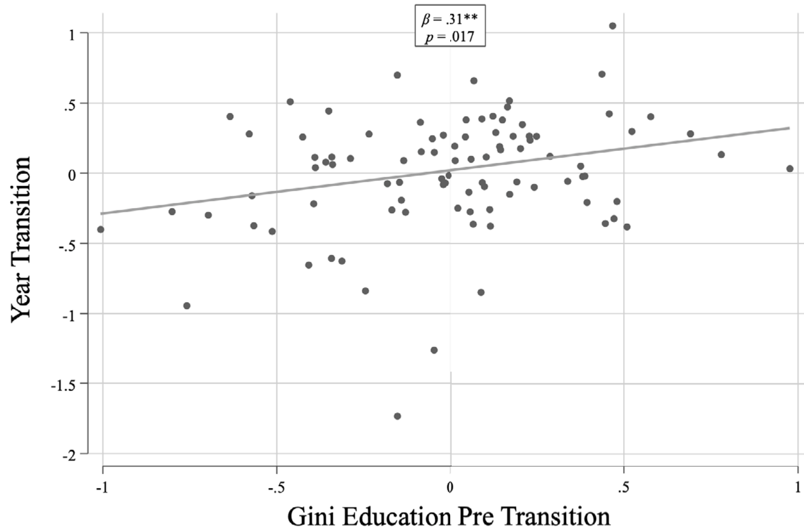
$$y_{it} = \zeta_i + \theta_t + \beta GiniEduc_{it-1} \cdot Post_{it} + \gamma_1 GiniEduc_{it-1} + \gamma_2 Post_{it} + \sum_j \phi_j X^j_{it} + \epsilon_{it}.$$

where y_{it} represents the natural logarithm of income *per capita* in country i at time t, while θ_t and ζ_i denote year- and country-fixed effects, respectively. The variable $Post_{it}$ is a dummy variable that takes the value of one from the first year in which country i undergoes the demographic transition. $GiniEduc_{it-1}$ measures inequality in education, as calculated by the Gini index over the five years preceding (from $t-1$ to $t-5$).[17] The model also includes a set of j controls, denoted X^j_{it},

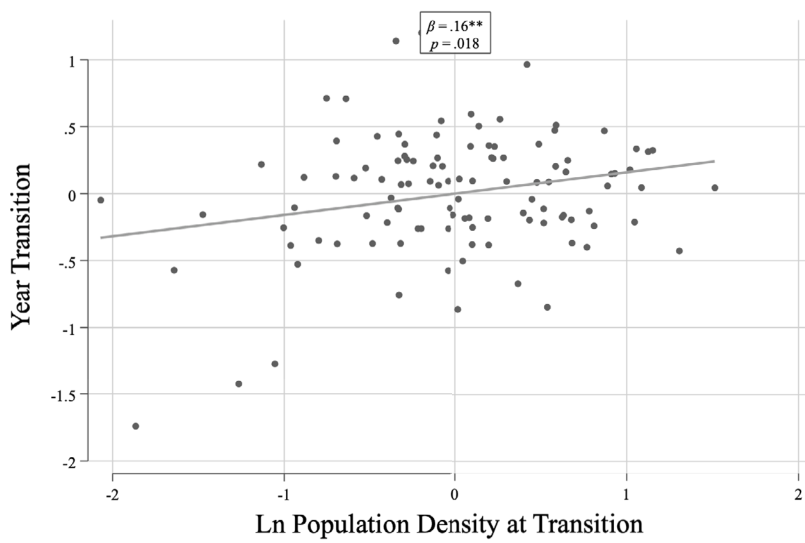
[15] This result hinges upon the Romer/Grossman–Helpman/Aghion–Howitt structure of technology growth, whose micro-foundations imply that individuals discover new ideas; therefore, the number of innovations is positively (but not linearly) linked to the number of people engaged in R&D. The critique by Jones (1995) of that class of models primarily hinges upon inconsistencies with the time-series evidence from industrialized economies. Thus, my model intends to explain the technology–growth nexus around the Industrial Revolution, which possibly followed a different dynamic as indicated in the literature (Cowan, 2011; Gordon, 2017).

[16] Data sources are described in Appendix Section Q.

[17] Similar results are obtained when using the Gini at time $t-1$ or applying different averaging windows.



(a) Human Capital Composition and the Timing of the Transition



(b) Population at the Time of the Transition

Fig. 4. Human capital composition, population, and the timing of the transition. Notes: The top panel shows a scatter plot of the relationship between the year of the demographic transition and inequality of education, measured by the Gini index in 5 years before the demographic transition. The underlying regression controls for agricultural suitability, average education in 5 years before the transition, and geographical region-fixed effects. The bottom panel shows a scatterplot of the relationship between the year of the demographic transition and the natural logarithm of population density. The underlying regression controls for agricultural suitability and geographical region-fixed effects. Variables are standardized.

which vary across specifications and are explained as follows. As the estimated model is a fixed-effect panel, and the outcome is measured in logarithms, the coefficient of interest, denoted as β, represents the average differential change in the logarithm of GDP *per capita* (i.e., the growth rate) in countries characterized by higher education inequality following the demographic transition. The results are presented in Table 1.

In Column (1) of Table 1, the estimated coefficient of interest is negative and statistically significant, indicating that countries with high education inequality before the demographic transition experienced slower economic growth during the post-Malthusian era. Moreover, Column (2) confirms a negative and significant estimated coefficient even after controlling for the average education levels more than the five years before (from $t-1$ to $t-5$). In Column (3), I further control for agricultural suitability, measured by the Caloric Suitability Index, which is time-invariant and thus interacted with year-fixed effects. The coefficient remains negative and statistically significant even in this less parsimonious specification. Its magnitude suggests that a 10 percentage point increase in inequality is associated with 0.4%pp less annual growth after the transition. Considering that the average growth rate after the transition is 0.3% (SD 0.8%), this is a substantial but reasonable size of the estimated coefficient. Furthermore, given that the Gini index of education proxies for fewer adopters, this empirical finding supports the model's predictions shown in panel 3 of Fig. 3.

The empirical evidence in this section has demonstrated that the data align with several critical hypotheses of the model, underscoring the significance of human capital composition in long-term growth. However, exercising caution in interpreting the empirical results is

Table 1
Human capital composition and post-transition economic growth.

	(1)	(2)	(3)
	Ln GDP *per capita*		
$GiniEducation_{t-1} \times PostTransition_t$	−0.0084*** (0.0020)	−0.0042*** (0.0015)	−0.0043*** (0.0015)
Observations	8720	8720	8720
R-squared	0.9304	0.9394	0.9401
Country FE	Y	Y	Y
Year FE	Y	Y	Y
$AverageEducation_{t-1}$	N	Y	Y
Ag. Suitab. × Year FE	N	N	Y

Notes: The table demonstrates that countries with higher education inequality before the transition exhibited slower growth rates following their respective demographic transitions. Standard errors clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

essential due to data limitations and challenges of econometric identification. Nevertheless, recent progress in historical data collection opens up promising avenues for further in-depth empirical inquiries on the link between human capital composition and long-term development in specific historical contexts.

For example, given that inventors are typically products of higher education, the availability of universities influence the costs associated with acquiring such education. Recent studies have examined the effects of the distribution of universities on local economic performance (Valero and Van Reenen, 2019), which could provide useful sources of exogenous variation. Moreover, historical censorship altered the returns on higher-level education, potentially offering valuable exogenous shocks to human capital the distribution (Blasutto and de la Croix, 2023). Furthermore, the prevalence and migration of inventors could offer valuable clues regarding the differences in the availability of highly skilled human capital (De la Croix et al., 2020). The cost of education for adopters is more closely related to the presence of public schools, mass education reforms, and discrepancy in school fees. These factors may provide additional sources of exogenous variation for empirical identification of the prevalence of adopters. Overall, these studies offer additional data and variations for further studies on the effects of human capital composition on long-term economic performance.

5. Conclusions

This study examines the impact of human capital composition on the timing of the transition from stagnation to growth, and the economy's long-term trajectory. Moreover, it offers a theoretical framework where the trade-off between higher and lower education within an economy includes a trade-off between creating and adopting new technologies. While highly educated individuals contributed to technological innovation, the lack of a sufficiently educated workforce to adopt those innovations hindered technology adoption and delayed the shift from stagnation to growth. Nevertheless, a large group of educated individuals in the labor force drives economic growth in the modern era and offsets the adverse effects of the delayed transition by facilitating technology adoption as innovation increases.

This study presents empirical regularities in the data that support key hypotheses of the model. Further, it demonstrates that human capital composition is crucial in explaining differences in the timing of the transition to modern growth and post-transition economic performance. Empirical identification and data limitation represent challenges whose comprehensive solutions are beyond the scope of this study and can be topics for future research. Nevertheless, this study offers novel insights into the development of these empirical tests and predictions about the potential overall effects of education reforms, which can have important implications for fertility decisions and long-term economic growth, by influencing the cost of education and the human capital composition.

Declaration of competing interest

None.

Data availability

I have provided a Link to Mendeley Data Repository

Human Capital Composition and Long-Run Economic Growth - Replication Files (Reference data) (Mendeley Data).

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT 3.5 in order to improve language and readability. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econmod.2024.106760.

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