Testing Unified Growth Theory: Technological Progress and the Child Quantity–Quality Tradeoff

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Abstract. A core mechanism of unified growth theory is that accelerating technological progress induces mass education and, through interaction with child quantity-quality substitution, a decline in fertility. Using unique new data for 21 OECD countries over the period 1750-2000, we test, for the first time, the validity of this core mechanism of unified growth theory. We measure a country's technological progress as patents per capita, R&D intensity, and investment in machinery, equipment and intellectual property products. While controlling for confounders, such as income growth, mortality, and the gender wage gap, we establish 1) a significant impact of technological progress on education (positive) and fertility (negative); 2) that accelerating technological progress stimulated the fertility transition; and 3) that the baseline results are supported in 2SLS regressions using genetic-distance weighted foreign patent-intensity, compulsory schooling years, and minimum working age as instruments.

Keywords: technological progress, fertility, education, quantity-quality tradeoff, unified growth theory.

JEL: O40, O30, N30, J10, I25.

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1. Introduction

Unified growth theory (UGT) suggests that long-run economic development over the entire course of human history can be explained by one consistent model rather than by separate theories tailored for specific periods of development. The theory, developed by Galor and Weil (2000) and extended and refined by Galor and Moav (2002), conceptualizes human economic history as a phase transition through three regimes, the Malthusian Regime, the Post-Malthusian Regime, and the Modern Growth Regime (see Galor, 2005, 2011, for an extensive discussion). Technological progress, driven by a gradual increase in population or a gradual increase in education (or both), eventually frees societies from the Malthusian Regime of stagnation at subsistence level and allows for both a gradual rise in income and increasing fertility rates during the Post-Malthusian Regime. The Modern Growth Regime is initiated when technological progress is sufficiently forceful to trigger an educational expansion and a fertility transition. During this phase, accelerating technological progress induces parents of later-born generations to invest more in education and to prefer a smaller number of offspring. Declining population growth and increasing technological progress through a better-educated workforce accelerate economic growth such that economies that successfully initiate the fertility transition take off at unprecedented growth rates and eventually converge towards a steady state of high, human-capital-driven economic growth.

Here, we test, for the first time, the validity of the core mechanism of UGT using unique new data for 21 OECD countries over the period 1750-2000. The core UGT mechanism consists of two elements: (i) a child quantity-quality (QQ) substitution at the household level that motivates parents to enhance their investment in their offspring's education; and (ii) a positive effect of technological progress on education. The perhaps surprising fact that the core mechanism of UGT has not been scrutinized empirically so far can be explained by the hitherto lack of data for technological progress and education investment over the relevant time period for sufficiently many countries.[1]

The QQ tradeoff is a rather broad phenomenon describing the negative association between fertility and investments in child quality, such as education. Evidence in favor of the QQ tradeoff thus only provides necessary but not sufficient support for UGT. This is so because other theories

[1]In this paper, we do not test the full general equilibrium model of UGT, which, aside from its core mechanism, consists of an aggregate production function, a production function for technological progress, general equilibrium conditions, and more. Specifically, we do not investigate how technological progress is produced.

of long-run development have been proposed that also employ the QQ tradeoff but not the technological progress mechanism. Probably the most popular alternative theory originates from Becker's (1960) theory of child quantity-quality substitution, which has been further developed by Becker and Lewis (1973). It proposes that rising income induces parents to opt for fewer children and spend more resources on their education (see Becker et al., 1990, and Moav, 2005, for a discussion in the context of long-run development). The subsequent literature shows that using the theory to predict the income-fertility nexus is more difficult than initially thought and requires additional assumptions about, for example, the utility function and the production functions for child quality and quantity (Jones et al., 2010). UGT additionally criticizes income-driven theories of fertility because they appear to be counter-factual with respect to the economic and demographic development in Western Europe where the decline in fertility occurred in the same decade despite significant cross-country income differences (Galor and Moav, 2002; Galor, 2005). UGT thus proposes a different cause of the QQ tradeoff: "In our model, parents also switch out of quantity and into quality, but do so not in response to the level of income but rather in response to technological progress" (Galor and Weil, 2000, p. 810).

Based essentially on the QQ tradeoff, other theories of the fertility transition and take-off have been proposed, such as theories of child mortality (Kalemli-Ozcan, 2002, Lagerloef, 2003a); child labor (Hazan and Berdugo, 2002); contraception (Bhattacharya and Chakraborty, 2017; Strulik, 2017); adult life expectancy (Soares, 2005; Cervellati and Sunde, 2015), and food prices and structural change (Strulik and Weisdorf, 2008). These theories, in the sense that they focus on long-run development from stagnation to modern growth, are also conceptualized as unified growth theories. The difference between these studies is the proposed mechanism that initiates and propels the QQ tradeoff. The unique feature of the canonical UGT is that the driver of the QQ tradeoff is identified as increasing technological progress, which induces more education and less demand for children. Here, we focus on the mechanism proposed by the canonical model of UGT (Galor and Weil, 2000; Galor and Moav, 2002).

A popular way to examine the child QQ tradeoff is to use the exogenous variation in fertility due to twin births. Several studies using this approach and micro-data from modern societies have found little or mixed support for the QQ tradeoff (e.g., Black et al., 2005; Caceres-Delpiano, 2006; Rosenzweig and Zhang, 2009; Angrist et al., 2010). These studies, however, do not take into consideration that, according to UGT, both education and fertility are endogenous. An unexpected variation in fertility violates the first order conditions of parental calculations from which the QQ tradeoff is derived. A true test of the QQ tradeoff would require an exogenous variation in the cost of children or the return to education (Galor, 2012).[2]

A few studies use long-run cross-country panel data to explore the determinants of the fertility transition and, indirectly, the QQ tradeoff. For the period 1960-1999, Lehr (2009) shows that fertility is negatively associated with secondary education and that it is positively associated with productivity increases at low stages of development and negatively at advanced stages. Murtin (2013) finds, for the period 1870-2000, that years of primary schooling (but neither income nor mortality) are a robust determinant of fertility. Herzer et al. (2012) show, for the period 1900-1999, that income growth causes fertility to decline and Dalgaard and Strulik (2013) show that the timing of the fertility transition is a powerful predictor of contemporary income differences and that the correlation between the year of the onset of the fertility transition and labor productivity is mediated by human capital accumulation. Chatterjee and Vogl (2018) match macro GDP data with micro fertility data and show that fertility declines with long-run growth. The finding of a negative association between fertility and growth supports UGT but does not constitute a strict test of its key mechanism. This is so because economic growth could be generated by various processes, such as opening to (transatlantic) trade, capital deepening, or the discovery of natural resources, i.e., processes that do not necessarily increase the return to education. The canonical UGT, however, hypothesizes that fertility declines due to technological progress and its impact on the return to education.

Here, we extend the literature in various directions. To test the model we collect annual data for 21 OECD countries over the period 1750–2010 and estimate whether the QQ tradeoff exists and how it is affected by technological progress, while controlling for a variety of other potential confounders, such as the mortality rate, the gender wage gap, and the level and the growth rate of per capita income. Technological progress is measured by the number of new patents per capita in the baseline regressions and by investment in machinery, equipment, and intellectual

[2] Klemp and Weisdorf (2018) find support for the QQ tradeoff during England's industrial revolution using the protogenesic interval (between marriage and first birth) as exogenous variation in fecundity. Bleakley and Lange (2009) provide evidence from hookworm eradication, conceptualized as a decline in the costs of education; Aaronson et al. (2014) provide evidence using improved access to education for African-American children in the U.S. south; and Bailey (2013) provides evidence using differences in access to oral contraceptives across US states in the 1960s and 1970s. Becker et al. (2010) demonstrate a QQ tradeoff in Prussia before the demographic transition with two-way causality between education and fertility. For Ireland in the early 20th century, Fernihough (2017) shows that fertility is negatively associated with voluntary enrollment in secondary school.

property products and R&D intensity as complementary measures of skill-biased technological change in the robustness section.

Testing the predictions of UGT is complicated by the length of time over which the data is required in order to cover the period starting from the onset of the First Industrial Revolution until the recent completion of the fertility transition. While recent data, starting from around 1960, are readily available from international organizations, the ease with which data can be accessed diminishes exponentially as we go back in time. Most of the early data sources are national statistical sources and specialized national studies that occasionally cover only some regions within countries. The most complex task has been to construct school enrollment rates because the data from national statistical agencies are mostly not available before the mid-19th century or later. Furthermore, private education, education by ambulant schools, and home education, which dominated national education well into the 19th century, are generally not accounted for in official statistical sources. Numerous sources are used to construct GERs and historical testimonies are used to understand the formal and informal school systems that prevailed before the introduction of formal mass education in the 19th century.

In order to establish the extent to which fertility is driven by technological progress through the channel of school enrollment, we use foreign patent-intensity weighted by genetic distance as an instrument, along with compulsory schooling and minimum working age. Finally, to gain further insights into the role of technological progress in the fertility transition, we test for momentum and threshold effects, i.e., we estimate the extent to which the impact of technological progress on fertility depends on its pace and its level and whether it affects fertility only when its level becomes sufficiently high.

The paper is organized as follows. In the next section, we review the household side of the canonical UGT model and derive the key hypotheses. In Section 3, we introduce the empirical model and our handling of simultaneous endogeneity of the fertility and education decisions; we also present the data set and examine long-run regularities in graphical analyses. Section 4 provides the regression results and Section 5 concludes.

2. The QQ Tradeoff in Unified Growth Theory

Consider the following model, based on Galor and Weil (2000) and Galor and Moav (2002). Suppose households have the following preferences:[3]

$$u_t = (1-\gamma)\log c_t + \gamma\left[\log n_t + \beta \log h_{t+1}\right], \tag{1}$$

in which c_t is consumption in period t, n_t is fertility, h_{t+1} is human capital per child in period $t+1$, γ is the utility weight of 'child services', $n_t h_{t+1}$, and β is a weight of child human capital, $\beta \in (0,1]$. Human capital is produced by parents' investment in education per child, e_{t+1}. Parents are endowed with h_t units of human capital and receive a potential income, $w_t h_t$, where w_t is the market wage per unit of human capital. Parents are endowed with one unit of time per period, which can be spent earning income or rearing children. Child rearing requires $\tau + e_{t+1}$ units of time, in which τ is essential time costs of child quantity and e_{t+1} is optional time costs of child quality. The implied budget constraint reads

$$c_t = \left[1-(\tau + e_{t+1})n_t\right] w_t h_t. \tag{2}$$

The human capital of the next generation depends on parents' investment in education and on technological change (the growth rate of technology) g_{t+1}, such that $h_{t+1} = h(e_{t+1}, g_{t+1})$. The production function of human capital satisfies the following assumptions: (i) education increases human capital, $h_e \equiv \partial h_{t+1}/\partial e_{t+1} > 0$; (ii) technological progress reduces human capital (makes knowledge obsolete), $h_g \equiv \partial h_{t+1}/\partial g_{t+1} < 0$; and (iii) technological progress increases the return on education, $h_{eg} \equiv \partial^2 h_{t+1}/\partial e_{t+1}\partial g_{t+1} > 0$.

Parents choose the levels of consumption and education that maximize utility, (1) subject to the budget constraint, (2), the non-negativity constraints, $n_t \geq 0$, $e_{t+1} \geq 0$, and a subsistence constraint $c_t \geq \bar{c}$. The first order conditions with respect to n_t and e_{t+1} are:

$$-\frac{(1-\gamma)(\tau + e_{t+1})}{1-(\tau+e_{t+1})n_t} + \frac{\gamma}{n_t} \leq 0, \tag{3}$$

$$-\frac{(1-\gamma)n_t}{1-(\tau+e_{t+1})n_t} + \beta\gamma\frac{h_e(e_{t+1}, g_{t+1})}{h(e_{t+1}, g_{t+1})} \leq 0, \tag{4}$$

[3] We do not consider the full dynamic general equilibrium models of Galor and Weil (2000) and Galor and Moav (2002). We focus on the household's decision problem, which is sufficient to elaborate the core UGT mechanism.

where (3) holds with equality when the subsistence constraint is not binding and (4) holds with equality when the education constraint is not binding. For $w_t h_t > \bar{c}$, we obtain from (3):[4]

$$n_t = \begin{cases} \left(1 - \frac{\bar{c}}{w_t h_t}\right) \frac{1}{\tau + e_{t+1}} & \text{if } (1-\gamma) w_t h_t < \bar{c} \\ \frac{\gamma}{\tau + e_{t+1}} & \text{otherwise.} \end{cases} \tag{5}$$

At the interior solution, households spend an income share of $1-\gamma$ on consumption and an income share of γ on children. If planned consumption falls below subsistence consumption, the subsistence constraint is invoked. If and only if the subsistence constraint binds, there exists a positive association between household income and fertility. Irrespective of whether the subsistence constraint binds, there exists a negative association between fertility and education: more expenditure on education is (partly) financed by lower fertility. The negative association between fertility and education is understood as child quantity-quality substitution or child quantity-quality (QQ) tradeoff (Galor and Weil, 2000; Galor and Moav, 2002; Galor, 2005). Of course, the QQ tradeoff is observable only when there is education. At the interior solution, the QQ tradeoff is observable independently of income, while at the corner solution, the QQ tradeoff is observed when income is held constant (i.e., controlling for income). Notice, furthermore, that equation (5) is *not* the solution to the model. It is just one first-order condition combined with a subsistence constraint. In particular, there is no causality going from education to fertility, nor from fertility to education. A central assumption of UGT is that the education and fertility decisions are taken simultaneously and are thus both endogenous. Exogenous variation in fertility, for example through unplanned and thus sub-optimal twin births, are interesting mechanisms to scrutinize a quantity-quality tradeoff but are of limited value for an empirical assessment of UGT (see Galor, 2012, for an extensive discussion).

While there exist many theories that motivate a child quantity-quality tradeoff, the defining element of UGT is the proposed trigger for education. Equation (5) becomes a solution to the model when it is considered together with the first order condition for education. Using (3), the first order condition for education can be simplified to:

$$G(e_{t+1}, g_{t+1}) = \beta(\tau + e_{t+1}) h_e(e_{t+1}, g_{t+1}) - h(e_{t+1}, g_{t+1}) \leq 0. \tag{6}$$

[4]For $w_t h_t \leq \bar{c}$, $n_t = 0$. As Galor and Weil (2000), we henceforth focus on the non-trivial solution.

Equation (6) establishes the solution for education since fertility is eliminated from the equation. The equation contains education as the only endogenous variable, while all other parameters and variables are considered to be exogenous from the household's perspective. Without further assumptions, the solution for education is not explicit. Its features, however, can be implicitly discussed. The key mechanism of UGT, namely that technological progress induces education is obtained from

$$\frac{\partial G}{\partial e_{t+1}} = \beta(\tau + e_{t+1})h_{ee} - (1-\beta)h_e < 0, \qquad \frac{\partial G}{\partial g_{t+1}} = \beta h_e(\tau + e_{t+1}) - h_g > 0.$$

When there is education, and thus $G = 0$, the implicit function theorem establishes a positive and causal impact of technological progress on education:

$$\frac{\mathrm{d}e_{t+1}}{\mathrm{d}g_{t+1}} = -\frac{\partial G/\partial g_{t+1}}{\partial G/\partial e_{t+1}} > 0. \tag{7}$$

Until this point the UGT of Galor and Weil (2000) and Galor and Moav (2002) coincide. The models differ in their assumptions about the composition of households. Galor and Weil (2000) consider a society of homogenous households (and simplify $\beta = 1$). They assume that the curvature of the education function ensures that $G(0,0) < 0$. This assumption provides a corner solution for education and generates the prediction that technological progress induces education only if its rate is high enough. This implies that there exists a (long) period in history without mass education because technological progress was too low. Observed education is explained outside the model by, for example, religious or cultural motives. Embedded in a macroeconomy, in which technological progress is driven by education and population size (through learning-by-doing), UGT explains a sequence of states of the world: a Malthusian regime where both education and consumption are at their corner solution; a Post-Malthusian regime where sufficiently high technological progress triggers education, but a positive association between income and fertility still prevails due to the binding subsistence constraint; and a Modern Growth regime in which education rises and fertility declines.

Galor and Moav (2002) consider a society of heterogeneous households that differ in the weights they put on child quality (β) in a specific way. For some, $G(0,0) < 0$, which renders behavior the same as in Galor and Weil (2000). For others, $G(0,0) = 0$, such that they always invest in education. Assuming that the subsistence constraint initially binds for all households, the model generates the same three regimes as the Galor and Weil (2000) model with the distinction that a positive association between technological progress and education and a negative association between technological progress and fertility is present at all times (albeit observable only for some individuals in the society).

Another result of the canonical UGT is that income (or income growth beyond that explained by technological progress) is *not* associated with education. This result could be modified by relaxing the assumption that children only incur time costs and/or the assumption that the returns and cost of education are not affected by parental education. The independence of the QQ tradeoff from income, however, is a result emphasized by UGT as a distinctive feature (e.g., Galor and Weil, 2000 p. 810; Galor and Moav, 2002, p. 1153). The QQ dependence on technological progress rather than income helps to explain why the countries of Western Europe experienced the fertility transition at about the same time despite their different levels of income per capita.

Inserting $e(g_{t+1})$ in (5), we obtain the solution for n_t, which contains fertility as the only endogenous variable, and technological progress and other parameters as exogenous determinants. Since fertility depends indirectly on technological progress, through education and the QQ tradeoff, UGT concludes that increasing technological progress leads to declining fertility. Specifically, we arrive at the following predictions of UGT:

(1) There exists a negative correlation between education and fertility (QQ tradeoff)

(2) (a) Technological progress, if high enough, has a positive impact on education (Galor-Weil)

(b) Technological progress always has a positive impact on education (Galor-Moav)

(3) Technological progress has a negative impact on fertility through education

(4) If technological progress becomes high enough, it triggers the fertility transition

(5) Income (or income growth not driven by technological progress) has no impact on education and, after the onset of the fertility transition, no impact on fertility

(6) Before the onset of the fertility transition, income has a positive impact on fertility

To the best of our knowledge, predictions (2)–(5) have so far never been tested empirically. Most of the literature focuses either on the Malthusian mechanism (6) or on the QQ tradeoff (1), which constitutes an essential prerequisite of UGT but is insufficient to describe the core mechanism. The study that comes perhaps closest to our analysis is the one by Chatterjee and Vogl (2018) who find a negative impact of long-run growth in income of the working age population on fertility in a panel of developing countries and interpret this as evidence for unified growth theory. Economic growth, however, is not the same as technological progress. Economic growth could increase, for example, by capital deepening, increasing labor force participation, increasing openness, discovery of natural resources, commodity price booms, or structural change that is independent of technological change. In this case, it would not trigger education, and unified growth theory would predict that it should have no impact on education. Here, we focus on technological progress and thereby on the mechanism that is at the core of unified growth theory. Income growth, however, may affect education and/or fertility independently of technological progress through channels not captured by unified growth theory. We thus include income growth as a potential confounder in our empirical analysis.

The preference and technology parameters of the model are likely to be country-specific and not necessarily time-invariant. Thus, we also include country fixed-effects and time fixed-effects in the regressions. We control for mortality, child labor, and female empowerment since these demographic variables have been suggested as being independent influences on fertility and education. Reverse causality is no issue since we measure technological progress at the same year as fertility and education forwarded ten years; assuming, consistent with the model, that the fertility and education decisions were made simultaneously but that the education decision becomes observable only 10 years later when the children could go to school. While the UGT model suggests that the level of income is not decisive for education and fertility after the onset of the fertility transition, other theories do (see Introduction) and, hence, we also control for the level of income in some of the regressions.

3. Empirical Method and Data

3.1. **Model Specification.** The following two models are estimated:

$$\log FER_{it} = \lambda_0 + \lambda_1 \log GER_{i,t+1} + \lambda_2 \log(Pat/Pop)_{it} + \lambda_3 \Delta \log(Y/Pop)_{it} + \lambda_4 \log CMR_{it} + \lambda_5 \log W_{it}^{Gap} + \phi_i + \varphi_t + \epsilon_{1,it}, \tag{8}$$

$$\log GER_{i,t+1} = \gamma_0 + \gamma_1 \log FER_{it} + \gamma_2 \log(Pat/Pop)_{it} + \gamma_3 \Delta \log(Y/Pop)_{it} + \gamma_4 \log CMR_{it} + \gamma_5 \log W_{it}^{Gap} + \phi_i + \varphi_t + \epsilon_{2,it}, \tag{9}$$

where FER is the general fertility rate; GER is the gross enrollment rate (henceforth GER) at primary and secondary levels; Pat is the number of new patents granted to residents in period t; Pop is population; Y is real GDP; CMR is the crude mortality rate, measured as the number of deaths per 1000 population; ϵ is a disturbance term; and $W^{Gap} = (W^M - W^F)/W^M$ is the gender wage gap, where W^M and W^F are hourly, weekly, or monthly wages of males and females; and ϕ_i and φ_t are country and time fixed-effects. Here, $GER_{i,t+1}$ refers to GER_{it}, forwarded 10 years. The model is estimated in non-overlapping 10-year intervals over the periods 1750-2010 (GER) and 1750-2000 (fertility). The sample period ends in the year 2000 in the fertility model to give room for the 10-year forwarded GER.

According to UGT and the child QQ tradeoff, the fertility and education decisions are taken simultaneously such that there exists no independent influence of fertility on education and vice versa once all potential drivers of fertility or education are accounted for. The right hand side variables GER and FER thus control for confounding channels through which fertility may impact education and vice versa.

The variables that potentially influence fertility and education according to the QQ model, are technological progress, mortality, economic growth, and the gender wage gap. Since technological progress, proxied by patent-intensity, is the key driver of the fertility transition in the UGT framework, we use various approaches to deal with potential endogeneity, as discussed in detail in the next sub-section (Section 3.2). The pooled seemingly unrelated regression estimator is used to account for cross-country residual correlation, the parameter estimates are corrected for cross-country heterogeneity and serial-correlation, and the model is estimated in non-overlapping 10-year intervals to filter out random and cyclical fluctuations and to allow for slow adjustment of the dependent variables to changes in the independent variables within each observation interval. Each variable is measured as an annualized average within each 10-year interval except for the growth rate of per capita income, which is measured as the annualized geometric growth rate over each 10-year interval.

The models are estimated over the period 1750-2000, as well as for shorter periods, to capture the fertility transition in full and to allow for the effects of temporary fertility spurts. Estimates that are concentrated in the transitional period 1880-1980, may be overly influenced by medium-term time trends; an effect that will be less pronounced over a longer time span. Furthermore, the efficiency gain from long historical data is crucial here because we estimate in non-overlapping

10-year intervals and, in some cases, in 5-year intervals. It is important to stress that GERs are used here as opposed to the commonly used educational attainment. Educational attainment is a stock that is determined by past enrollment rates and the exit of older workers from the labor force into retirement and, as such, is determined in the past and is little influenced by contemporary decisions. GER is the relevant outcome variable because it refers to education at the time at which the schooling decision is made.

The gender wage gap is included in the models as it affects the opportunity costs of having children relative to the income of the household (Galor and Weil, 1996). Galor (2005), for example, argues that the reduced gender wage gap starting during the Second Industrial Revolution, contributed to the fertility transition (see also Lagerloef, 2003b; Prettner and Strulik, 2016; Strulik, 2019). Based on the identification strategy of Schultz (1985), Madsen et al. (2020) show that females gained a comparative advantage following the grain invasion from the new world which started in the second half of the 19th century. Crude mortality is included in the models since parents care about net fertility and because some strands of the demographics literature argue that the fertility transition was fueled by the mortality transition (see, e.g., Guinnane, 2011). Since data on age-dependent mortality are scant before 1860, we proxy the survival probability of children by the crude mortality rate. It is also worth stressing again that the same control variables are included in Eqs. (8) and (9) because the QQ model assumes that the fertility and educational decisions are taken jointly.

Technological progress is measured by patent-intensity, where the number of patents is normalized by population following second-generation Schumpeterian growth models (see, e.g., Peretto, 1998; Ha and Howitt, 2007; Madsen, 2008). If, on average, technological progress is skill biased, we would expect $\log GER_{i,t+1}$ to be significantly positively related to $\log(Pat/Pop)_{it}$. Patents are excellent indicators of technological progress because they have been through screening, are generally accurate, and are available far back in time. Furthermore, patent-intensity is a stationary process with low persistence, which means that its significance in the regressions is not an outcome of positive or negative time-trends it has in common with education and fertility. The downside of patents as technology indicators is that not all inventions are patented and that inventions are highly heterogeneous. The heterogeneity of patents is not a problem if they are in large numbers; however, it is a problem when the number of patents is small. Since patent counts are new patent flows, patent-intensity measures technological progress and not the level of technology.

We use R&D-intensity and the income share of net investment in machinery, equipment, and intellectual property products as alternative and complementary indicators of skill-biased technological progress in the robustness section. R&D-intensity is measured as real R&D divided by real GDP, noting that R&D and GDP are deflated by quite different deflators (see, for details, Madsen et al., 2021). The R&D expenditure, which is from Madsen et al. (2021), is estimated from various R&D indicators, such as the number of R&D workers, government spending on R&D, government spending on salaries to univesities, and enrollment in tertiary education. R&D has the advantage over patents in that it implicitly weights innovations by R&D effort, whereas patent counts weight all innovations equally regardless of the significance of the innovation. Conversely, R&D is likely to be less exogeneous than patents because investment in R&D is partly determined by R&D opportunities, such as the education of the workforce. Before WWII or slightly earlier, most R&D was carried out in public and private universities – institutions that were often financed by joint efforts of royals, industrialists, and governments (Madsen et al., 2021).

The increasing share of real investment in machinery and equipment in total real income in the OECD countries since the onset of the Industrial Revolution reflects, to a large extent skill-biased technological progress that is driven by new investment-specific technology. Krusell et al. (2000), for example, argue that demand for skills accelerates in response to increasing investment in machinery and equipment. In support of their theory, they find that the elasticity of substitution between machinery and equipment capital and unskilled labor is significantly higher than that of capital equipment and skilled labor, suggesting that machinery capital and skilled labor are complements in production. Similarly, Caselli (1999) develops a theory in which technological revolutions increase the demand for workers who are able to switch to sectors that benefit from new technologies. Caselli argues that skilled labor and capital investment were complementary during the First and the Second Industrial Revolutions. Overall, there is support in the literature for the idea that industrial revolutions are associated with increasing demand for skilled labor (see, for further references and discussion, Acemoglu, 2002; Galor, 2011).

It has been argued that technological progress could be unskilled-biased during the First Industrial Revolution such that technological advances during this period did not trigger a fertility transition (Galor, 2005). Here, we will show that even if technological progress during the First Industrial Revolution were skill-biased, it would not have been forceful enough to trigger a fertility transition. As shown in the data section 3.3 below, patent intensity was approximately 50 times larger during the Second Industrial Revolution than during the First Industrial Revolution. Furthermore, the real price of investment in machinery and equipment was flat before the 1870s, pointing towards insignificant investment-specific technological progress.

Per capita income growth and technological progress are both included in the models to make a clear distinction between growth driven by technological progress and growth driven by factors unrelated to technological progress, such as saving-induced capital deepening, land clearing, increasing labor force participation rates, Smithian growth (increasing division of labor), foreign trade, gold discoveries, commodity booms, terms of trade shocks etc. Essentially, per capita growth is included in the model to control for the impact of economic development on fertility and education.

Finally, one may question why we need to estimate both equations (8) and (9) since one is a mirror image of the other. There are two reasons why it may be useful to estimate both models. First, since the ideal conditions are never met in an uncontrolled environment, the derived elasticities will differ across the two models. Following the classical errors-in-variables problem, for example, the correlation between the measurement error of the dependent variable and the residual is assumed to be zero, while this is not the case for the independent variables. The same reasoning applies to endogeneity due to the exclusion of unobserved control variables that differ between the two equations. Although we have included more control variables than almost all other long-run studies of the fertility transition, there are surely unobserved variables we have not been able to control for, such as cultural and environmental factors, for example. To preserve space, most of our estimates are based on the fertility model.

As explained in Section 2, equations (8) and (9) are derived from a standard UGT model following Galor and Weil (2000). According to this literature, the increasing rate of technological progress during industrialization increased the returns to human capital and, consequently, changed the incentives to trade quantity for quality in the fertility decision. It is worth stressing that it is technological progress and not the level of technology that is crucial for the fertility transition in the models of Galor and Weil (2000) and Galor and Moav (2002). In the robustness section, we allow for the coefficients of technological progress to vary over time and across regimes and investigate whether technological progress always exerted an influence on fertility and education or only when its level was sufficiently high, as predicted by the Galor-Weil model.

3.2. **Identification.** According to unified growth theory, the focus variables are fertility, education, and skill-biased technological progress (Galor, 2005). While the fertility and education decisions are taken simultaneously, there is a subtle causal relationship between fertility and education in UGT. According to UGT, only education depends directly on technological progress, which is the mechanism that incentivizes parents to increase the resources spent on education of their children which, consequently, forces parents to reduce fertility. Thus, technological progress affects fertility through its impact on education (and not vice versa). We instrument the GERs based on the following first-stage regression:

$$\log GER_{i,t+1} = \alpha_1 \log(Pat/Pop)^F_{it} + \alpha_2 \log Comp^{min}_{it} + \alpha_3 \log WA^{min}_{it} + \mathbf{W}'\theta + \epsilon_{3,it}, \tag{10}$$

in which $Comp^{min}$ is years of compulsory education; WA^{min} is the minimum working age; $(Pat/Pop)^F$ is foreign patent-intensity weighted by the square root of genetic proximity; and $\mathbf{W}$ is a vector of the variables contained in the second-stage regression. Ultimately, we are interested in the impact of technological progress on fertility through education. Compulsory education and minimum working age are added to the setup in order to improve the reliability of the regression results.

We do not carry out traditional 2SLS regressions in which all three instruments are included in the instrument set. Instead, we use the 'falsification adaptive set' (FAS) approach of Masten and Poirier (2021) in which we derive the baseline identified set of point estimates under which the baseline model is not refuted. The benefits of the FAS approach are that 1) it complements traditional overidentification tests by including the variation in estimates obtained from alternative nonfalsified models; and 2) it excludes invalid instruments that would otherwise bias the parameter estimates of the structural model. To achieve this, we estimate the 2SLS regressions using different combinations of the instruments while, at the same time, controlling for the instruments that are excluded from the first-stage regression in the second-stage regression, as discussed in detail in the 2SLS regressions in Section 4.2. This approach gives two additional insights over the traditional 2SLS approach. First, it provides interval estimates of the coefficients of the instrumented variable, *GER*, and second, it roots out weak instruments from the first-stage regression while, at the same time, controlling for the excluded weak instrument(s) in the second-stage regression. Note that the FAS analysis is not a test of instrument validity but rather an analysis of instrument relevance and the sensitivity of the structural parameters to different combinations of instruments.

The minimum working age is included as a factor that affects the opportunity costs of education. Doepke (2004), for example, argues that child labor laws were influential for the demographic transition. Like the minimum working age, the number of compulsory school years reduces the opportunity cost of education. A key question is whether compulsory schooling and minimum working age violate the exclusion restriction and are exogenous. There are reasons to believe that the exclusion restriction is, to some extent, violated, but not to such a degree that these variables cannot be considered to be semi-solid instruments. Whereas per capita income and institutional quality were similar for Portugal, Spain, Finland, Norway and Denmark the schooling and minimum working age laws and the attitudes towards education were markedly different.[5] The downside of these instruments is that the minimum working age and compulsory school years are influenced by the processes of economic development; thus violating the exogeneity condition. As argued by Galor and Moav (2006), for example, the mercantile and industrial capitalists, who stood to gain from a more educated labor force, lobbied for the provision of universal public education. This is particularly true for England after the mid-19th century, when the urban elite realized that English education was lagging behind the other Western European countries (Galor and Moav, 2006). By acknowledging that the instruments vary in their relevance and non-excludability, the FAS approach is informative because it gives us some confidence that the true but unobserved causal effect is not too far from the obtained range of 2SLS estimates.

By instrumenting GER by foreign patents, we implicitly assume that foreign patents affect fertility through either GER or domestic patent intensity. Following Spolaore and Wacziarg (2009), we assume that technology spillovers are stronger among genetically closely related countries

[5]Statutory laws, introduced already in the 1730s in Denmark and Norway, were major forces behind the expansion of education starting more than 150 years before the onset of the fertility transition in these two countries (see the Data Appendix for a detailed discussion and references). For Spain in the mid-16th century, by contrast, the church authorities decided that the unrestricted production of books had to be stopped; essentially to prevent the expansion of Protestantism (Nalle, 1989). The decision resulted in a list of prohibited books in 1551 and door-to-door interviews by inquisitors gradually increased in intensity after this year to prevent the spread of potentially dangerous ideas. This intervention broke the upward trend in the Spanish literacy rates before 1551 and had long-lasting effects on education in Spain (Nalle, 1989). Furthermore, several scholarly articles argue that the Napoleonic Wars carried the seeds for the expansion of mass education in Europe during the 19th century (see, for a recent example, Aghion et al., 2019).

than genetically distant countries, because genetically close populations tend to have comparable habits, beliefs, customs, and values and these traits are transmitted from one generation to the next. Testing various channels through which technologies are transmitted internationally, Madsen and Farhadi (2018) find that the genetic proximity channel came out favorably over other transmission channels. In our OLS regressions, domestic patent intensity has a significant impact on fertility even after enrollment rates are accounted for. Therefore, we control for domestic patent intensity in the second stage of the IV regressions to ensure that foreign patents affect fertility through GER and the coefficients of GER are unbiased. In principle, foreign patent-intensity may affect fertility through domestic income growth; however, we do not include income growth in the 2SLS regressions because it is endogenous and we show in the baseline regressions that income growth does not affect the parameter estimates of the focus variables.

3.3. **Data.** The data construction has been a Herculan task because the data availability exponentially diminishes as we go back in time and most of the data from international sources are generally first available from the second half of the 19th century or later. While the quality of the historical data are not of the contemporary standard, the economy was much simpler to measure in the pre-industrial period than after. It was, for example, easy to keep track of births because almost everyone in the community was a member of the church, which kept records, a great many of which survived, and migration was often limited to the neighboring towns. The variety of goods and professions was also a small fraction of what it is today. The historical data are collected for the following 21 OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the US. Here, we provide a broad overview of the data while the data construction and sources are detailed in the Data Appendix.

For the gender wage gap, our approach is to include the wages for as many sectors and professions as possible to ensure that the data are as representative of the whole economy as possible. While gender wage data are available for broad sectors of the economy from the mid-20th century, the data coverage is mostly for manufacturing and agriculture in the approximate period 1850-1950 and for agriculture before 1850. The data indicate that the gender wage gap is not sensitive to payment intervals (hourly, weekly or monthly) and that it is similar in the manufacturing and service sectors. However, the wage gap is generally lower for agriculture than for other sectors of the economy; a problem that is catered for in the estimates by ensuring a smooth transition from agriculture to manufacturing and by splicing the overlapping data. Most of the pre-WWI data are daily wages in the agricultural sector, after which manufacturing gradually takes over as the dominant non-service sector.

The general fertility rate, FER, is calculated as the total number of live births per 1,000 females of reproductive age between 15 and 44 years in a population per year. This is a more precise measure of fertility than the crude birth rate (births per 1000 population) because FER uses the female population aged 15 to 44 years in the denominator and, therefore, is not affected by the significantly changing age structure of the population during demographic transitions. Before being published by national statistical agencies, the fertility data are predominantly reconstructions from church registers and then scaled up to national levels.

School enrollment rates, which are constructed by Madsen (2022), are estimated as school enrollment divided by the population of the relevant school age cohort. The data from standard sources used in the literature, such as Mitchell (2007), provide generally poor coverage during the 19th century and no data are available earlier than 1830. Mitchell (2007) obtains almost all his data from statistical yearbooks. However, the data in statistical yearbooks are generally inaccurate before and during the fertility transition because they often omit private education, education of ambulant schools, and home education. Furthermore, this data often show implausible jumps or growth spurts (often triggered by the changes in number of grades included at each level in the data), changes in the number of included districts, failure to make a clear distinction between vocational training and non-vocational education, and often show inconsistencies across censuses.

Numerous sources are used to construct GERs and historical testimonies are used to understand the formal and informal school system that prevailed before the introduction of formal mass education in the 19th century. In Norway and in Denmark before compulsory education was introduced in the early 19th century, for example, no official school enrollment data are available (see Madsen, 2022 for a detailed discussion and references). This does not mean that education was non-existent during this period and earlier. Reforms were introduced as early as 1736 and 1739 in Denmark and Norway. For example, the introduction of the confirmation reform in 1736 in Denmark, in which certain literacy standards were required for a child to be confirmed in the Protestant tradition, gave teenagers exceptionally strong incentives to learn reading skills from new-established schools, the clergy, and parents. Anybody who was not confirmed was prohibited from owning real estate, leasing land, and could not be married or become a soldier (Madsen, 2022). To give the children the opportunity to meet the required learning standard for confirmation, the 1739 school reform in Norway lead to the establishment of ambulant schools, in which teachers taught in each school district two months a year to cater for isolated children in tiny settlements all over the country. Enrollment was close to 100%, suggesting a very effective coverage (Madsen, 2022). Without detailed country studies, the resort to routine retropolation of the GERs leads to large errors and misleading trajectories in a period that is essential for understanding the educational expansion and the fertility transition.

Genetic distance-weighted research intensity spillovers are estimated from the following weighting scheme:

$$\left(\frac{Pat}{Pop}\right)^F_{it} = \sum_{j=1}^{31} \sqrt{\frac{1}{D^{gen}_{ij}}} \left(\frac{Pat}{Pop}\right)_{jt}, \quad j \neq i,$$

where D^{Gen}_{ij} is the genetic distance between countries i and j, and is measured as the distance between ethnic groups with the largest shares of the population in each country in a pair (denoted FST by Spolaore and Wacziarg, 2009), and is normalized by the average distance in the sample so that the weights sum to one. The weighting is assumed to be inversely related to the square root of distance to ensure that long distances get higher weights than in the case in which $1/D^{gen}$ is used as weights.[6]

3.4. **Graphical Analysis.** Figures 1 and 2 display the average general fertility rate and the crude mortality rate for the OECD countries, where the dashed lines signify 95% confidence interval bands around the average. Separate graphs for the UK, the US, France, and Germany are presented in the online Appendix. For the average country, the fertility transition took place over the approximate period 1880-1980; though interrupted by an increase in fertility from the depth of the Great Depression in 1932/33 to 1964. The fertility transition occurred roughly at the same time in all Western countries. France deviated somewhat from this pattern in that its fertility decline started already at the turn of the 19th century (see Figure 1 in the online Appendix). However, the French fertility decline was initially slow and it accelerated from about the 1880s such that the early decline can be understood as a gravitation towards

[6]Taking square roots implies that the genetic distance between Germany and China gets the weight of $1261^{-1/2} = 35.5$ and the genetic distance between Germany and Denmark gets the weight of $38^{-1/2} = 6.1$, which means that Denmark gets 6.1 times higher weight than China when $(D^{gen})^{-1/2}$ is used in the weighting scheme as opposed to 33.2 times more weight when $(D^{gen})^{-1}$ is used as weights.

Table 1. Summary Statistics

	1750-2000 10-Year Mean	1750-2000 10-Year Std. Dev.	1805-2000 5-Year Mean	1805-2000 5-Year Std. Dev.
$\log GER_{it}$	3.28	1.24	3.65	0.93
$\log FER_{it}$	4.75	0.37	4.68	0.38
$\log(Pat/Pop)_{it}$	-3.97	3.13	-2.87	2.37
$\log(Pat/Pop)^F_{it}$	-0.48	2.14	0.39	1.42
$\log(R\&D/Y)_{it}$			-6.34	1.69
$\log(I^{M\&E}/Y)_{it}$			-4.18	1.21
$\log(I^{B\&S}/Y)_{it}$			-3.05	0.83
$\log CMR_{it}$	2.82	0.42	2.72	0.42
$\log W^{Gap}_{it}$	-0.90	0.33	-0.95	0.36
$\Delta\log(Y/Pop)_{it}$	0.01	0.03	0.02	0.03
$\log WA^{Min}_{it}$	1.35	1.27		
$\log Comp^{Min}_{it}$	1.01	1.05		
Obs.	546		861	

Notes. GER is gross enrollment rate at primary and secondary levels; FER is general fertility rate; Pat/Pop is patent intensity; $R\&D/Y$ is research intensity; CMR is crude mortality rate; W^{Gap} is gender wage gap; Y/Pop is per capita income; $Comp^{Min}$ is compulsory school years; WA^{Min} is the minimum working age; $I^{M\&E}$ is real investment in machinery, equipment, and intellectual property products; $I^{B\&S}$ is investment in non-residential building and structures.

the mean of the OECD countries and, as such, it does not constitute a fertility transition. Furthermore, the mortality rate in France was well above the average before the epidemiological transition in the second half of the 19th century (see Figure 1 in the online Appendix). Although gradually converging to the OECD average up until the 1870s, the French mortality rate was 11% higher than the OECD average over the period 1800-1871. This mortality gap exemplifies the importance of allowing for mortality in the regressions.

Figure 1: General Fertility Rate

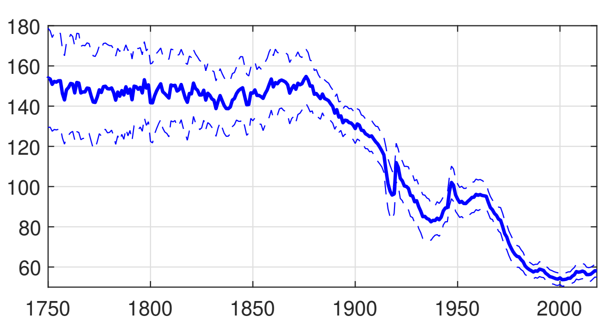
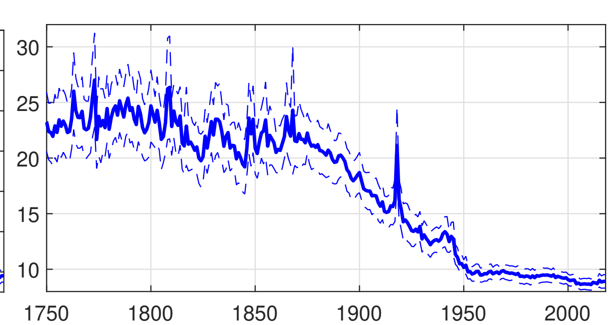


Figure 2: Crude Mortality Rate



Unweighted averages for the 21 OECD countries in our sample. The general fertility rate, FER, is measured as the total number of live births per 1,000 females of reproductive age between 15 and 44 years in a population per year. The crude mortality rate is measured as the number of deaths per 1000 population. The dashed lines signify 95% confidence interval bands around the average.

Like FER, the crude mortality rate, CMR, starts a sharp downturn in 1880; however, the downturn is approximately completed in 1950, which is 30 years before the fertility transition is completed. If one accepts that FER reacts to CMR with a lag, then CMR is a potential candidate to explain the fertility transition as stressed by some strands of the demographic literature (Cleland, 2001; Guinnane, 2011; Kalemli-Ozcan, 2003). This conclusion may have been reached by comparing the data for France and Italy over the past three centuries, for which CMR and FER have moved in tandem for most of the time. However, the relationship between CMR and FER is mostly weak for the other OECD countries. Regressing FER on CMR and a time-trend for each individual country in our sample yields coefficients of CMRs that are statistically insignificant for Canada, the US, Belgium, Denmark, Norway, Sweden, Finland, the Netherlands and Switzerland. In the estimates below we find a significantly positive relationship between FER and CMR; however, the declining CMR only accounts for approximately a quarter of the fertility transition. As shown below, this means that declining mortality cannot explain declining *net* fertility.

Primary and secondary gross enrollment rates, GERs, display three growth regimes as seen from Figure 3: 1750-1820 (slow growth); 1820-1913 (fast growth); and 1913-1980 (moderate growth). The increase is driven predominantly by primary education before WWII and secondary education thereafter. However, as for fertility, the educational trajectories vary substantially across countries: They increased rapidly in countries with an early fertility transition (Canada, the US, Belgium, the Netherlands, Scandinavia, and Switzerland). Among the most populous countries, the US school enrollment rate was well above that of the other countries until WWI when the UK caught up with the US, while France and Germany were much slower to catch up to the UK and the US (see Figure 3 in the online Appendix).

The gender wage gap, W^{Gap}, fluctuated around a relatively constant level over the period 1800-1880, decreased slightly up to 1940, and has since decreased substantially (see Figure 4). While the post-1940 decrease is consistent across all countries, Belgium, Italy, Spain, and Sweden experienced a slight decline during most of the 19th century and France experienced a decline in the gap throughout most of the 20th century (online Appendix Figure 4). A decrease experienced by Italy and Spain in the 19th century, which was associated with a slight decrease in FER, may partly have been driven by convergence towards the OECD mean, noting that

Figure 3: Primary and Secondary GER

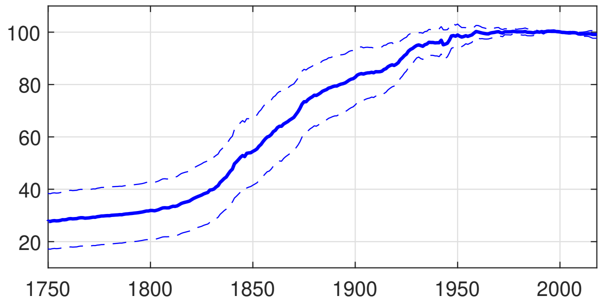
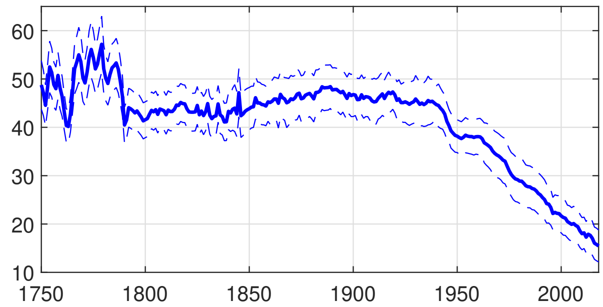


Figure 4: Gender Wage Gap



Averages for OECD countries. GER measures the percentage of the population aged 6-17 that is enrolled in primary and secondary education. The gender wage gap is measured as $W^{Gap} = (W^M - W^F) \cdot 100/W^M$, where W^M and W^F are wages of males and females. Wage gap stated in percentages. The dashed lines signify 95% confidence interval bands around the average.

Figure 5: Patent-Population Ratio

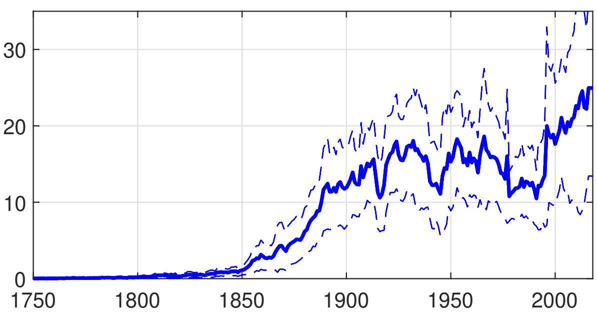
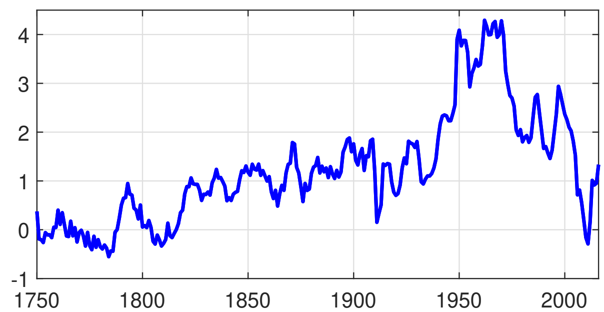


Figure 6: Per Capita Income Growth



Averages for OECD countries. The patent-population ratio is measured as the number of patents granted per 1000 population. The annual per capita income growth rate is measured in 7-year centered averages, where the three-year endpoints are actual values; it is stated as a percentage. the dashed lines signify 95% confidence interval bands around the average.

FER and W^{Gap} for these two countries were well above the OECD average at the turn of the 19th century.

Figure 5 displays patent intensity, which is the key variable in unified growth theory to the extent that it proxies skill-biased technological progress. Starting from a low level, patent intensity increased markedly over the period 1850-1935; particularly in the 1880s, during which the fertility transition started in most of the sample countries. Since the 1880s, the average patent-intensity fluctuated around a relatively constant level until the 1990s when it increased further following the ICT revolution. Common for all countries in the sample is that technological progress was slow before 1850; thereafter, however, the path and the year of take-off differed across countries. Austria, Belgium, France, and the US, for example, experienced an early, but gradual, increase in patent intensity from 1850, whereas it occurred at a later stage in Finland and, particularly, in Greece, Ireland, and Portugal.

Finally, Figure 6 shows that per capita income growth is, on average, close to zero up to the end of the Napoleonic Wars in 1815, increases to an approximate mean of 1% over the period 1816-1940, increases further to 3.5% during the Golden Period 1950-1973, and has since reverted back to the level that prevailed before the Golden Period. If the fertility transition was partly caused by economic development, we would expect shifts in per capita income growth to predate or coincide with shifts in the fertility rate. However, this is not what we observe: On average, the fertility transition started 60 years after income growth jumped from zero to one percent after 1815; and the post-WWII baby boom coincided with the growth expansion during the Golden Period. Comparing Figures 5 and 6, we observe that the period around the onset of the fertility transition (around 1880) is characterized by steeply increasing new patents, i.e., an acceleration of technological progress. We do not observe such an acceleration for income growth in the relevant period.

4. Regression Results

4.1. **Baseline Regressions.** The results of estimating the fertility equation, (8), are presented in Table 2. The result in column (1) establishes a highly significantly negative bivariate relationship between FER_t and GER_{t+1}, as predicted by UGT. In column (2), fertility is regressed on patent intensity as a simple bivariate relationship. The coefficient of $(Pat/Pop)_t$ is highly significantly negative as predicted by UGT. The coefficients of $(Pat/Pop)_t$ and GER_{t+1} both remain highly significant when they are included in the same model (column (3)). The coefficient of patent-intensity is 63% larger in the regression without GER_{t+1}, suggesting that a substantial fraction of technological progress reduces fertility through education, as predicted by UGT. However, in contrast to the predictions of UGT, there is still a significant negative residual impact of skill-biased technological progress on fertility.

There are three possible explanations for the remaining negative association with patent-intensity when GER_{t+1} is included in the model. First, UGT is only a partial explanation for the fertility transition. Technological progress can influence fertility by reducing the comparative advantage of child labor; thus, reducing the fertility incentive (Hazan and Berdugo, 2002). Second, technological progress promotes the diffusion of modern cultures that value high fertility

Table 2. Fertility Regressions

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
$\log GER_{t+1}$	-0.176***		-0.128***	-0.075***		-0.060***		-0.052***	-0.064***	-0.010***		-0.020***	-0.226***	
	(0.000)		(0.000)	(0.000)		(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	
	[0.875]		[0.744]	[0.446]		[0.290]		[0.352]	[0.360]	[0.664]		[0.383]	[0.549]	
$\log(Pat/Pop)_t$		-0.052***	-0.032***	-0.016***	-0.024***	-0.014***	-0.020***	-0.016***	-0.014***	-0.025***	-0.039***	-0.017***	-0.061***	-0.126***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
		[0.738]	[0.591]	[0.281]	[0.438]	[0.249]	[0.370]	[0.316]	[0.237]	[0.505]	[0.619]	[0.652]	[0.435]	[0.874]
$\log CMR_t$				0.452***	0.510***	0.426***	0.453***	0.426***	0.350***			0.593***		
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			(0.000)		
$\log W_t^{Gap}$				0.087***	0.112***	0.078***	0.086***	0.091***	0.111***			0.135***		
				(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.000)			(0.000)		
$\Delta\log(Y/Pop)_t$				0.019	0.019							-0.104***		
				(0.628)	(0.59)							(0.000)		
$\log(Y/Pop)_t$						-0.050***	-0.062***							
						(0.000)	(0.000)							
$D^{Reh}\log(W/P)_t$								0.016***						
								(0.000)						
$\log(W/P)_t$								-0.035***						
								(0.000)						
$D^{Reh}(R/W)_t$													-0.0005**	-0.0001
													(0.035)	(0.134)
$D^{Reh}D^{UK}(R/W)_t$													0.0008***	0.0007**
													(0.000)	(0.018)
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	N	N	N	Y	Y	Y
Period	1750-2000	1750-2000	1750-2000	1750-2000	1750-2000	1750-2000	1750-2000	1750-2000	1750-2000	1750-2000	1750-2000	1750-2000	1750-2000	1750-2000
Frequency	10-Year	10-Year	10-Year	10-Year	10-Year	10-Year	10-Year	10-Year	10-Year	10-Year	10-Year	20-Year	10-Year	10-Year
# Countries	21	21	21	21	21	21	21	21	21	21	21	21	5	5
Obs.	546	546	546	546	546	546	546	546	546	546	546	546	130	130

Notes. p-values in parentheses and partial correlation coefficients in square brackets. The data are measured in 10-year non-overlapping intervals except in column (12) where the data are measured in 20-year averages but estimated in 10-year intervals. The SUR estimator is used and the parameter estimates are corrected for heteroscedasticity and serial correlation. Time-dummies are included in all regressions and country fixed-effects are included in the regressions marked with 'Y'. The dependent variable is the log of the general fertility rate; GER is gross enrollment rates at primary and secondary levels; FER is general fertility rate; Pat/Pop is patent-intensity; CMR is crude mortality rate; W^{Gap} is gender wage gap; Y/Pop is per capita income; R-W is the rent-wage ratio; D^{UK} is a dummy variable taking the value of one for the UK, and zero otherwise; W/P is real wages of blue-collar workers; and D^{Reh} is a dummy variable taking the value of one before the fertility transition and zero thereafter, where the year at which the fertility transition commences is taken from Reher (2004). *** = significant at 1%; ** = significant at 5%; * = significant at 10%.

less without affecting values on education. Spolaore and Wacziarg (2022), for example, find that the fertility decline starting from the 19th century resulted from a gradual diffusion of new fertility behavior from French-speaking regions to the rest of Europe. Third, measurement errors of fertility, school enrollment and skill-biased technological progress may have biased the parameter estimates and, therefore, contributed to the finding that patent-intensity remains significant when education is allowed for in the fertility-regressions. School enrollment, for example, is an incomplete measure of human capital, which in turn is likely positively related to the innovative activity. Furthermore, patent-intensity is an imperfect proxy for skill-biased technological progress, partly because some technological epochs promoted unskilled-biased technological progress. Improved machinery often increases the productivity of unskilled labor more than that of skilled labor and although some manual labor is replaced by machines, the technology-induced creation of new tasks may well overcompensate the employment opportunities of unskilled labor (Goldin and Katz, 1998; Acemoglu and Restrepo, 2018).

Considering the income variables, income growth exerts no significant influence on fertility in the 10-year interval estimate. In the 20-year interval estimate, when fluctuations due to depressions, wars and normal business cycle fluctuations are more smoothed out than in the 10-year estimates, the coefficient of growth is significantly negative; note, however, that the economic effects of growth are minuscule: The approximately 1.0-1.5% growth rate over the considered period kept the fertility rate down by 0.1-0.15%.

To investigate whether the level of income of the urban blue collar population affects fertility in the Malthusian regime, we extend the model with real wages covering the entire estimation period and real wages multiplied by a dummy variable, D^{Reh}, that takes the value of one before the fertility transition and zero thereafter, where the year at which the fertility transition commences is taken from Reher (2004). We use real wages instead of per capita income because per capita income was, to a large extent, driven up by the increasing land rent per hectare after 1700, while real wages of skilled and unskilled labor showed only a modest increase (Madsen and Strulik, 2021). Thus, the increasing per capita income up to the onset of the fertility transition does not reflect the income of the masses but that of the landed class. The coefficient of real wages covering the entire period is significantly negative, while it is significantly positive in the period leading up to the fertility transition (column (8)). Summing the coefficients of real wages in the overall period and the pre-transition period yields a negative effect of real wages on fertility.

From these results we can conclude that earnings of urban blue-collar workers exert negative effects on fertility, but significantly less so before the fertility transition, which is not consistent with the Malthusian theory. However, the urban wages are unlikely to be representative for wages in rural areas. For England, for instance, real wages of urban workers increased after 1750 while they were stagnant in the rural sector well into the 19th century (Madsen et al., 2010). Furthermore, the coefficients of real wages are likely biased in a negative direction because of a negative feed-back effect of fertility on income. Madsen et al. (2020), for example, find that income is significantly negatively affected by fertility.

Country fixed-effects are excluded from the estimates in columns (9)-(11), which means that the parameter estimates are jointly determined by between-country and within-country variation. The absolute values of the coefficients are slightly lower than their country fixed-effects counterparts. Comparing the regressions in columns (10) and (11) with and without GER, the coefficients of patent intensity and their associated partial correlation coefficients increase by 56% and 23% when GER is excluded from the regression; thus giving further support to the transition mechanism of UGT. When all fixed effects are excluded from the models, we arrive at the results presented in the online Table A1. The results are close to the baseline results except for the coefficient of crude mortality rate, which is significantly lower than the estimates in Table 2 (coefficient = 0.25), suggesting that the time-dummies capture the effects of unobserved omitted variables or, more likely, they capture the gap between the crude mortality rate, *CMR*, and mortality of children since the relevant decision variable is the survival probability. Importantly, however, the coefficients of the focus variables are robust to this consideration.

In column (12) the data are measured in 20-year intervals and, like the baseline regressions, estimated in 10-year frequencies for efficiency gains, noting that the standard errors are corrected for the first-order moving-average process in the error terms that emerge from the first-order overlap of the residuals. The estimation results are consistent with the baseline regressions except for the coefficient of economic growth, which is now significantly negative.

Finally, we include income inequality, as it may potentially hinder human capital accumulation because credit frictions bind under higher income inequality (see, e.g., Galor and Zeira, 1993; Galor and Moav, 2004). Conversely, by furthering the income of the landed class, higher inequality may simultaneously increase fertility and education because of differentiated fertility rates across income classes. Galor and Moav (2002), for example, argue that individuals who were wealthier had higher fertility rates in the pre-industrial period. Hence, in the early stages of development, the Malthusian pressure provided an evolutionary advantage to individuals whose preferences were biased toward offspring whose characteristics were complementary to the growth process. Empirically, Clark and Hamilton (2006) find that the net fertility of the wealthy during the 17th century was nearly twice that of the society as a whole in England. Clark and Cummins (2015) find that the positive association between wealth and fertility disappears after approximately 1780.

To test whether income inequality influences the fertility-education nexus, we include the rent-wage ratio, R-W, multiplied by a dummy variable taking the value of one before the fertility transition and zero thereafter, as a confounder in the last two columns in Table 2 (the year of the fertility transition is from Reher, 2004). Rents are measured as agricultural land rent per hectare and wages as daily wages of agricultural workers. The R-W ratio is a measure of income inequality for agricultural economies where landlords live off land rents while the working class lives off their labor. Due to data availability, the country sample is limited to the following five countries: France, the Netherlands, Portugal, Spain and the UK. We include the R-W ratio as a separate term for the UK because the inequality effect may have been stronger in the UK than elsewhere given its early industrialization.

The coefficient of the R-W ratio is significantly negative for the entire sample when education and patent-intensity are both included in the regression (column (13)). When GER is excluded from the regression, the R-W ratio for the whole sample is rendered insignificant, potentially because school enrollment is an important omitted variable that is correlated with the R-W ratio. For the UK, the R-W ratio is positive in both regressions. Though significantly positive, the fertility elasticity of income inequality is minuscule, perhaps because the landed class/labor population ratio was low. Consistent with the other estimates in Table 2, the size of the coefficient of patent-intensity doubles when GER is excluded from the estimates. Since this conclusion is unaltered when the R-W ratio is excluded from the regression (the results are not shown), we can conclude that the principal results are robust to a narrower country selection and the inclusion of income inequality between unskilled workers and the landed class.

Table 3. Education Regressions

	1	2	3	4	5	6	7	8	9	10	11	12
$\log FER_t$	-0.746***		-0.515***	-0.341***		-0.468***	-0.211***		-0.420***	-0.280***	-1.087***	
	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	
	[0.866]		[0.699]	[0.627]		[0.795]	[0.459]		[0.631]	[0.518]	[0.736]	
$\log(Pat/Pop)_t$		0.076***	0.063***	0.042***	0.172***	0.153***	0.123***	0.078***	0.072***	0.063***	0.058***	0.128***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
		[0.788]	[0.698]	[0.718]	[0.962]	[0.941]	[0.8889]	[0.762]	[0.737]	[0.714]	[0.354]	[0.639]
$\log CMR_t$				-0.664***			-0.593***			-0.539***		
				(0.000)			(0.000)			(0.000)		
$\log W_t^{Gap}$				-0.136***			-0.354***			-0.147***		
				(0.000)			(0.000)			(0.000)		
$\Delta \log(Y/Pop)_t$				-0.073			-0.0337***			-0.026		
				(0.273)			(0.009)			(0.704)		
$D^{Reh}(R/W)_t$											-0.0001***	-0.0001**
											(0.004)	(0.003)
$D^{Reh}D^{UK}(R/W)_t$											0.0001***	0.0000
											(0.074)	(0.482)
Country FE	Y	Y		Y	Y	Y	Y	N	N	N	Y	Y
Period	1750-2010	1750-2010	1750-2010	1750-2010	1750-2010	1750-2010	1750-2010	1750-2010	1750-2010	1750-2010	1750-2010	1750-2010
# Countries	21	21	21	21	21	21	21	21	21	21	5	5
Frequency	10-Year	10-Year	10-Year	10-Year	20-Year	20-Year	20-Year	10-Year	10-Year	10-Year	10-Year	10-Year
Obs.	567	567	567	567	567	567	567	567	567	567	130	130

Notes. p-values in parentheses and partial correlation coefficients in square brackets. The dependent variable is $\log GER_{t+1}$. The data are measured in 10-year non-overlapping intervals except in columns (5)-(7) where the data are measured in 20-year averages but estimated in 10-year intervals. The SUR estimator is used and the parameter estimates are corrected for heteroscedasticity and serial correlation. Time-dummies are included in all regressions and country fixed-effects are included in the regressions marked with 'Y'. GER is gross enrollment rates at primary and secondary levels; FER is general fertility rate; Pat/Pop is patent-intensity; CMR is crude mortality rate; W^{Gap} is gender wage gap; Y/Pop is per capita income; and R-W is the rent-wage ratio; D^{Reh} is a dummy variable taking the value of one before the fertility transition as dated by Reher (2004), and zero after the fertility transition. *** = significant at 1%; ** = significant at 5%; * = significant at 10%.

The results of estimating the GER model given by equation (9) are presented in Table 3. The coefficient estimates are consistent with those of the fertility model, noting that their absolute values are substantially larger in magnitude than their counterparts in the fertility regression, which, to a large extent, reflects that the standard deviation of GER is 1.24 while it is 0.37 for the general fertility rate. The coefficients of fertility and patent intensity are all highly significant regardless of model specification. The coefficients of patent-intensity are reduced when fertility is included in the regression and further reduced when the remaining confounders are included in the estimates.

The reduction in the coefficient of patent intensity when fertility is included as a regressor, however, need not mean that fertility is the variable through which factor-biased technological progress influences education. Since, under the maintained hypothesis of UGT, the coefficient of the fertility rate reflects reverse causality running from GER, the coefficient of patent-intensity is downward biased when fertility is included in the regression. Despite this, the coefficient of patent intensity remains highly significantly positive. The inclusion of the fertility rate in the regression, however, can be justified on the ground that it captures alternative confounding mechanisms through which patent-intensity and fertility rates could be negatively related. For instance, lower current fertility rates could partly reflect higher educational attainment of the current and previous generations (hence, the relationship with current patent intensity), and the impact of current fertility on enrollment rates in the next generation could potentially capture the latent influence of intergenerational transmission of "cultural attitudes" towards education on the next generation.

The magnitude of the coefficients of fertility and patent-intensity are relatively stable across the specifications in the 10-year interval regressions. By contrast, the coefficients of fertility (patent-intensity) are significantly smaller (larger) in the 20-year than the 10-year interval estimates, suggesting that the QQ tradeoff is more prevalent at medium-term than at long-term frequencies. However, regardless of whether the model is estimated using 10- or 20-year averages, the results give support for UGT.

The rent-wage ratio, R-W, interacted with the dummy variable taking the value of one before the fertility transition and zero thereafter, is included in the regressions in the last two columns in Table 3 (recall that the country sample is limited to five countries). The coefficient of the R-W ratio is significantly negative for the entire sample regardless of whether FER is included in the regression (columns (11) and (12)). Consistent with the other estimates in Table 2, the size of the coefficient of patent-intensity doubles when FER is excluded from the estimates.

4.2. **2SLS Estimates.** As stated above, we use the 'falsification adaptive set' (FAS) approach of Masten and Poirier (2021), to find a plausible range of the coefficient of the coefficient of GERs in which the baseline model is not refuted. The FAS approach proceeds in two steps. In the first step, the quality of each instrument is assessed, while model uncertainty is investigated in the second step. To achieve this, different combinations of instruments for GERs are used, while the instruments that are excluded from the first-stage regression are controlled for in the second-stage regression. The instruments, which are omitted from the first-stage regression, are included in the second-stage regression to overcome an omitted variable bias of the coefficient of GER because these variables, by assumption, influence fertility through GERs – a channel that is not catered for in the first-stage prediction of GERs since they are omitted from the instrument set. The main purpose of this section is to corroborate the result that technological progress is the main channel through which school enrollments reduce fertility.

The 2SLS regressions are presented in Table 4, where the second-stage parameter estimates of GERs and patent-intensity are presented in the upper panel and the first-stage results are in the lower panel. All confounders are included in the estimates, but, except for those of the omitted instruments, their estimated parameters are not shown for brevity. First, consider the first-stage regressions. Each instrument satisfies the relevance criteria as indicated by the F-tests (columns (1)-(3)). However, the coefficients of years of compulsory education are rendered insignificant when foreign patent-intensity is included in the regressions in columns (5) and (7), suggesting that the compulsory school age should be included as a control variable in the structural equation, but excluded from the first-stage regression. The statistical significance of the coefficient of minimum working age in the first-stage regression reduces from the 1% to the 5% levels when foreign patent-intensity is included in the model, giving some indication that minimum working age is a relatively weak instrument for GERs. In all cases, Sargan's tests for overidentifying restrictions are insignificant at conventional significance levels, suggesting that the instruments are uncorrelated with the errors in the second-stage regression and/or that variables are omitted from the structural model.

The second-stage regressions in the upper panel provide some insight into parameter uncertainty following the FAS approach. Excluding the estimates in which the compulsory schooling age is included in the instrument set, the coefficients of GERs are in the range between -0.108

Table 4. IV Regressions

	1	2	3	4	5	6	7
				Second Stage			
$\log GER_t$	-0.070***	-0.108***	-0.207***	-0.231***	-0.225***	-0.108***	-0.248***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.186]	[0.328]	[0.581]	[0.662]	[0.641]	[0.369]	[0.369]
$\log(Pat/Pop)_t$	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log Comp^{Min}$		-0.019***	-0.019***	-0.019***			
		(0.000)	(0.000)	(0.000)			
$\log WA^{Min}$	-0.028***		-0.028***		-0.024***		
	(0.000)		(0.000)		(0.000)		
$\log(Pat/Pop)_t^F$	-0.068***	-0.068***				-0.068***	
	(0.000)	(0.000)				(0.000)	
Instruments				**First stage**			
$\log Comp^{Min}$	0.279***				0.071	0.227***	0.063
	(0.000)				(0.19)	(0.000)	(0.243)
$\log WA^{Min}$		0.256***		0.102**		0.213***	0.098**
		(0.000)		(0.029)		(0.000)	(0.036)
$\log(Pat/Pop)_t^F$			0.330***	0.303***	0.311***		0.286***
			(0.000)	(0.000)	(0.000)		(0.000)
F-Stat.	28.1	30.2	111.4	58.5	56.6	24.9	118.5
Sargan				1.53	1.09	0.38	1.31
Obs.	546	546	546	546	546	546	546

Notes. The dependent variable is fertility, $\log FER_t$, in the second stage-regressions; and education, $\log GER_t$, in the first-stage regressions. p-values in parentheses. All the confounders, and instruments that are excluded from the first-stage regression, and fixed-effects are included in all the second stage regressions, but not shown. The estimation period is 1750-2000. The SUR estimator is used in the structural regressions, and the parameter estimates are corrected for heteroscedasticity and serial correlation. FER is general fertility rate; Pat/Pop is patent intensity; Pat/Pop^F is genetic-weighted foreign patent intensity; $Comp^{min}$ is years of compulsory education; WA^{min} is minimum working age; F-test is an F-test for excluded instruments; Sargan is Sagan's test for overidentifying restrictions distributed as a $\chi^2(1)$ under the null hypothesis that overidentifying restrictions may not be violated. *** = significant at 1%; ** = significant at 5%; * = significant at 10%.

and -0.231, suggesting significantly negative effects of education on fertility in all cases. Furthermore, the coefficients of patent-intensity are constant at -0.008 across all estimates because the instruments excluded from the first-stage regressions are contained in the second stage regressions. Compared to the fertility regression in column (4) in Table 2 in which all confounders are included in the model, the coefficients of patent-intensity of -0.008 in the 2SLS regressions are half the magnitude of that of the OLS-regressions. Conversely, the coefficient of the GER in the fertility regression in column (4) in Table 2 (-0.075), is lower than its range between -0.108 and -0.231 in the 2SLS estimates.

The finding that the coefficients of GERs are more negative in the 2SLS than in the OLS estimates may partly be related to the usual suspect – the attenuation bias. However, the issue is more subtle than that. As argued above, school enrollments are imperfect proxies for human capital. In particular, GERs exclude the higher end of the skill distribution and the cultural traits that incentivise innovation. Since these factors are, to some extent, captured by patent-intensity, we get that the absolute values of the coefficients of GERs are underestimated and that the coefficients of patent-intensity are overestimated in the OLS estimates. This possibility gains support from the OLS estimates in Table 2 in which the absolute values of coefficients of GERs shrink substantially when patent-intensity is included in the estimates. The higher order dimension of human capital that is not contained in school enrollment, is likely to be captured by the foreign patent-intensity of cultural neighbors in the 2SLS regressions.

The results that foreign patent intensity has the strongest statistical power in the 2SLS regressions and, at the same time, generates the largest negative coefficient of GERs in the second-stage regression, suggest that technological progress is a main channel through which school enrollments reduce fertility, as predicted by UGT. This stands in contrast to the years of compulsory schooling and minimum working age that do not violate the standard relevance and overidentifying restriction criteria when foreign patent-intensity is excluded from the instrument set. However, when confronted by foreign patent-intensity, their significance declines; so much so that the years of compulsory schooling variable ends up being excluded from the instrument set in the FAS analysis.

Overall, four main conclusions emerge from our FAS analysis: First, the evidence suggests that the compulsory schooling instrument is the most questionable, and should be used only as a control. Second, the qualitative conclusions based on the OLS estimates that GERs have an impact on fertility, are not overturned in the FAS analysis. Third, the results suggest that there is a causal negative effect from enrollment rates to fertility rates that appears to be driven by the increased demand for human capital associated with skill-biased technological progress. Fourth, since skill-biased technological progress could also be partially reflected by compulsory schooling laws and the minimum working age, we cannot claim that it is the dominant channel through which the full effect of education on fertility comes about.

4.3. **Alternative Technology Indicators and Placebo Tests.** In this subsection, we complement patent-intensity with real investment in machinery, equipment, and intellectual property products relative to real GDP, $I^{M\&E}/Y$, and R&D-intensity, $R\&D/Y$, to check the robustness of the predictions of UGT and to check for potential complementarities between different types of technologies. Furthermore, we undertake placebo tests to investigate whether the $I^{M\&E}/Y$-path

is driven predominantly by saving behavior or by economic development and not by investment-specific technological progress. All estimates in this subsection are based on post-1800 data because the additional technology indicators are first available from 1800 for almost all countries. Except for the regression in the first two columns, we estimate in five-year non-overlapping intervals in this section to ensure that the number of observations per country is sufficiently large for the SUR estimator to be operative (T needs to exceed N for identification of the cross-country residual correlation).

We start up with the baseline fertility model in 10-year intervals using the standard fixed-effects estimator. The results, which are presented in the first two columns in Table 5, are comparable to those of the baseline regression: The coefficients of education and patent-intensity are significantly negative and the absolute value of the coefficient of patent intensity doubles when education is excluded from the model. In columns (3) and (4), the model is estimated in 5-year non-overlapping intervals. Compared to the 10-year estimates in the first two columns, the coefficients of school enrollment are close in magnitude, while the coefficients of patent-intensity are significantly lower in the 5-year than the 10-year interval estimates. The relatively low coefficients of patent-intensity in the 5-year estimates are, to a large degree, driven by the slow adjustment of fertility to technology shocks.

When patent-intensity is measured in 10-year averages, but the model is estimated in 5-year observation intervals in column (4), its coefficient comes close to those of the regressions in 10-year observation intervals (the results are not shown). Focusing on the period 1850-1880, shortly before the fertility transition started, patent-intensity doubled (see Figure 5), resulting in a 29% decrease in fertility based on the estimates in column (4). This suggests that the marked technological progress around the onset of the Second Industrial Revolution was influential for the fertility transition. In sum, while the magnitude of effects depends on the choice of period, technology indicator and model specification, all of our results suggest that technological progress was an important impetus on the fertility transition.

The regressions with R&D-intensity as the technology indicator are presented in columns (5) and (6) in Table 5. The coefficients of GERs and R&D-intensity are significantly negative and comparable to those of the baseline regressions. Turning to the last technology indicator in column (7), the coefficient of $I^{M\&E}/Y$ is highly significantly negative, as we would expect if its evolution is predominantly driven by investment-specific technological progress. Economically,

Table 5. Alternative Technology Indicators, Fertility Model

	1	2	3	4	5	6	7	8	9	10	11	12	13
$\log GER_{t+1}$	-0.190***		-0.209***		-0.158***		-0.209***		-0.226***	-0.244***	-0.144***		-0.097***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	(0.000)	(0.000)		(0.000)
	[0.380]		[0.538]		[0.423]		[0.533]		[0.587]	[0.651]	[0.352]		[0.234]
$\log(Pat/Pop)_t$	-0.048***	-0.094***	-0.012***	-0.029***							-0.006***	-0.011***	-0.006**
	(0.000)	(0.000)	(0.000)	(0.000)							(0.000)	(0.000)	(0.011)
	[0.276]	[0.574]	[0.191]	[0.388]							[0.105]	[0.174]	[0.105]
$\log(R\&D/Y)_t$					-0.070***	-0.111***					-0.067***	-0.096***	-0.054***
					(0.000)	(0.000)					(0.000)	(0.000)	(0.000)
					[0.436]	[0.640]					[0.409]	[0.581]	[0.308]
$\log(I^{M\&E}/Y)_t$							-0.032***	-0.087***	-0.055***		-0.018***	-0.036***	-0.157**
							(0.000)	(0.000)	(0.000)		(0.005)	(0.000)	(0.024)
							[0.190]	[0.484]	[0.297]		[0.010]	[0.196]	[0.008]
$\log(I^{B\&S}/Y)_t$									0.069***	0.039***			
									(0.000)	(0.000)			
$\log CMR_t$													0.140***
													(0.000)
$\log W_t^{Gap}$													0.191***
													(0.000)
$\Delta\log(Y/Pop)_t$													0.100*
													(0.089)
Period	1800-2000	1800-2000	1805-2005	1805-2005	1805-2005	1805-2005	1805-2005	1805-2005	1805-2005	1805-2005	1805-2005	1805-2005	1805-2005
Estimator	FE	FE	SUR	SUR	SUR	SUR	SUR	SUR	SUR	SUR	SUR	SUR	SUR
Frequency	10-Year	10-Year	5-year	5-year	5-year	5-year	5-year	5-year	5-year	5-year	5-year	5-year	5-year
# Countries	21	21	21	21	21	21	21	21	21	21	21	21	21
Obs.	441	441	861	861	861	861	861	861	861	861	861	861	861

Notes. p-values in parentheses and partial correlation coefficients in square brackets. The dependent variable is the log of fertility. The parameter estimates are corrected for heteroscedasticity and serial correlation. Time fixed effects and country fixed effects are included in all regressions. GER is gross enrollment rates at primary and secondary levels; FER is general fertility rate; Pat/Pop is patent-intensity; $(R\&D/Y)$ is research intensity; $(I^{M\&E}/Y)$ is the share of real investment in machinery, equipment, and intellectual property products in real GDP, $(I^{B\&S}/Y)$ is the investment in non-residential buildings and structures in total GDP; CMR is crude mortality rate; W^{Gap} is gender wage gap; Y/Pop is per capita income. *** = significant at 1%; ** = significant at 5%; * = significant at 10%.

the approximately 250% increase in $I^{M\&E}/Y$ over the period 1880-1980 has resulted in an 11% decline of the fertility rate for the average OECD country. When education is excluded from the regression, the absolute value of the coefficient of $I^{M\&E}/Y$ more than doubles, suggesting that most of investment-specific technological progress affects fertility through education.

To check for the possibility that the coefficient of $I^{M\&E}/Y$ is driven by factors that are unrelated to skill-biased technological progress, such as saving behavior and economic development, we undertake a placebo test in which the share of gross investment in non-residential buildings and structures in total GDP, $I^{B\&S}/Y$, is included in the regressions with and without controlling for $I^{M\&E}/Y$. Krusell et al. (2000), for example, restrict investment-specific technological progress to zero in their theoretical and empirical framework: Investment-specific technological progress stems entirely from investment in machinery and equipment, suggesting that increases in $I^{B\&S}/Y$ are not influenced by investment-specific technological progress but are driven by saving behavior.

The coefficient of $I^{B\&S}/Y$ is significantly positive regardless of whether $I^{M\&E}/Y$ is included in the regression (columns (9) and (10) in Table 5). If $I^{B\&S}/Y$ was driven by economic development and savings, then we would expect it to be a significantly negatively associated with fertility.

The positive fertility-effects of $I^{B\&S}/Y$ indicate that building capital and unskilled labor are complements. Furthermore, the non-negative coefficient of $I^{B\&S}/Y$ suggests that investment-specific technological progress affects fertility quite independently of economic development and more thriftiness. A further implication of these results is that the coefficients of $I^{M\&E}/Y$ and, presumably, also those of the other technology indicators are not likely to be significantly biased due to endogeneity induced by unobserved confounding factors of economic development.

All three technology indicators are included in the regressions in the last three columns. The coefficients of all three technology indicators are significantly negative in the regressions regardless of whether school enrollment and all confounders are included in the models, pointing towards some complementarity between the technology indicators. Quantitatively, a one standard deviation increase in the technology indicators in the regressions where they are included individually as the only non-deterministic variable results in the following proportional change in the general fertility rate: -6.9% (patent-intensity); -19.3% (R&D-intensity); and -10.5% (machinery investment ratio). When the technology indicators are jointly included in the model, the total effects of a one standard deviation increase in the technology indicators is associated with a 23.2% reduction in the general fertility rate. These results suggest that technological progress, in general, is influential for reducing fertility.

The coefficient of mortality is 0.14 in the regression in the last column in Table 5, which is substantially lower than its baseline counterpart of 0.45 in Table 2; a result that further corroborates the conclusion that declining mortality did not contribute to the decline in *net* fertility. This result is predominantly driven by the restricted estimation period, 1800-2000, and not by the inclusion of R&D-intensity and the machinery investment-ratio in the estimates in Table 5. The coefficient of mortality increases modestly from 0.14 to 0.195 when R&D-intensity and the machinery investment ratio are excluded from the regression (the results are not shown).

The magnitude of the coefficient of the gender wage gap of 0.191, by contrast, is almost twice the size of that of the baseline regression of 0.112 in Table 2, column (4), and twice the size if R&D-intensity and the machinery investment ratio are excluded from the model. Using the coefficient estimate from Table 5, the approximately 50% decline in the gender wage gap over the period 1880-1980, has contributed to a 9.5% decline in the fertility rate; a result that is consistent with the theory of Galor and Weil (1996) and the findings of Madsen et al. (2020).

4.4. **Technological Growth Spurts.** In this section, we extend the estimates to allow for time- and regime-varying effects of skill-biased technological progress. This enables us to examine whether the impact of technological progress on fertility and education became operative with the onset of the fertility transition, as predicted by the Galor-Weil model. For brevity, we focus on the fertility regressions, as doing so also allows us to explore the hypothesis that technological progress, if it becomes high enough, triggers the fertility transition.

First, consider a more informal approach, where equation (8) without confounders is extended to include the interaction between patent-intensity and time-dummies. Patent-intensity is measured in 20-year moving averages to smooth out the change in the coefficients of the interaction terms. The sum of each coefficient of the interaction between time-dummies and patent-intensity and the coefficient of patent-intensity yield the overall technological progress elasticities of fertility for each period. The Galor-Weil (2000) model predicts these elasticities to be zero before the fertility transition because technological progress is too low.

The evolution of the technology elasticities is shown by the solid line in Figure 7. Dashed lines show confidence bands with two times the standard deviation of the coefficients. Up to 1860, the elasticities are mostly insignificantly different from zero, whereas they are significantly negative over the period of the fertility transition 1870-1980, which is consistent with the prediction of the Galor-Weil model. The time-profile shown in Figure 7 remains unchanged if all confounders are included in the regression from which the elasticities are derived and if the countries with delayed fertility transitions relative to the average country, viz Greece, Ireland, Italy, Portugal, and Spain, are excluded from the regressions.

Figure 7: Tech. Time-Effects

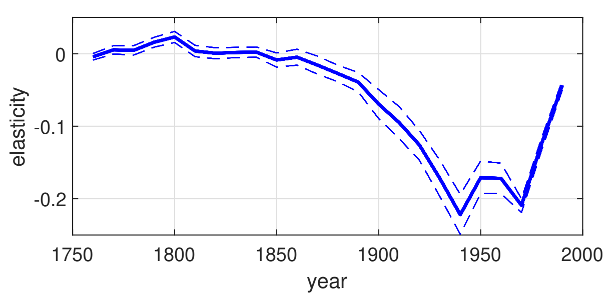
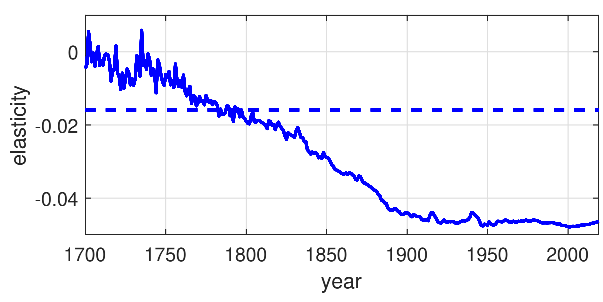


Figure 8: Tech. Threshold-Effects



Notes. FIGURE 7. The figure shows technological progress elasticities of fertility for each period, estimated as the sum of each coefficient of the time-dummies interacted by patent-intensity and the coefficient of patent-intensity based on estimates of equation (8) without confounders, extended with the interaction between 20-year moving averages of patent-intensity and time-dummies. FIGURE 8. The figure shows technological progress elasticities of fertility based on the elasticities derived from equation (12) (solid line) and the coefficient of patent-intensity in column (4) in Table 2 (dashed line).

Next, to test the trigger-hypothesis more formally, we construct a dummy variable that takes the value of one when patent-intensity goes beyond a certain threshold level and zero otherwise. We refine equation (8) to allow the coefficient of patent intensity to vary in the two regimes:

$$\log FER_{it} = \mu_0 + \mu_1 \log GER_{i,t+1} + \mu_2 \log(Pat/Pop)_{it} + \mu_3 \Delta \log(Y/Pop)_{it} + \mu_4 \log CMR_{it}$$
$$+ \mu_5 \log W_{it}^{Gap} + \zeta_1 D^{TP} \log(Pat/Pop)_{it} + \zeta_2 (1 - D^{TP}) \log(Pat/Pop)_{it} + \phi_i + \varphi_t + \epsilon_{1,it}, \quad (11)$$

where $D^{TP} = 1$ when $(Pat/Pop) \geq 0.15$, and zero otherwise. The threshold is set to 0.15 because then the Akaike Information Criterion reaches its maximum in a grid search of (11) without confounders.

The results of estimating (11) are shown in columns (1)-(4) in Table 6. Columns (1) and (2) are without confounders, and in columns (3) and (4), where patent-intensity is the sole explanatory variable, the coefficients of patent-intensity are significantly negative in the high-technology regime and insignificant in the low-technology regime; results that are consistent with the Galor-Weil model. These results suggest that the fertility choice is little affected by technology-induced returns to education in regimes with slow technological progress and the influence of factors such as the availability and the cost of education, access to reading material, and cultural factors that influence education.

In order to derive non-constant elasticities from our main regression, we extend equation (8) to include a squared term for technological progress, $[\log(Pat/Pop)]^2$. Results are shown in column (5) in Table 6. The quadratic term is statistically significantly negative and economically large. This suggests that the patent-elasticity of fertility is not constant but depends on the level at which technological progress advances. An increasing patent-intensity increases the downward pressure of technological progress on fertility. From the estimates in column (5), we arrive at the following time-varying elasticity:

$$\frac{\partial \log(FER)_t}{\partial \log(Pat/Pop)_t} = -0.049 - 0.006 \log(Pat/Pop)_t^{Avr}, \quad (12)$$

where $(Pat/Pop))^{Avr}$ is the average patent-intensity across countries in our sample. By setting this equation to zero, we find the level of patent intensity at which the variation in patent-intensity has no effect on fertility. Based on the estimates in column (6), this is found at the

Table 6. Thresholds and Dynamic Effects

	1	2	3	4	5	6	7	8	9
$\log GER_t$	-0.130***	-0.047***			-0.130***	-0.060***	-0.151**		-0.164**
	(0.000)	(0.000)			(0.000)	(0.000)	(0.013)		(0.034)
	[0.626]	[0.386]			[0.462]	[0.422]			
$\log(Pat/Pop)_t$					-0.049***	-0.013***	-0.093***	-0.121***	0.016
					(0.490)	(0.000)	(0.000)	(0.000)	(0.187)
					[0.369]	[0.266]			
$\log(Pat/Pop)_t^2$					-0.003***				
					(0.000)				
					[0.266]				
$D^{TP}\log(Pat/Pop)_t$	-0.175***	-0.071***	-0.121**	-0.151***					
	(0.000)	(0.000)	(0.013)	(0.004)					
	[0.473]	[0.219]	[0.120]	[0.146]					
$(1-D^{TP})\log(Pat/Pop)_t$	-0.054	0.067	0.182	0.043					
	(0.305)	(0.175)	(0.242)	(0.771)					
	[0.046]	[0.062]	[0.057]	[0.015]					
$\log CMR_t$		0.434***			0.468***	0.179***			0.497**
		(0.000)			(0.000)	(0.000)			(0.013)
$\log CMR_{t-4}$						0.362***			
						(0.000)			
$\log W_t^{Gap}$		0.623***			0.095***	0.102***			0.007
		(0.000)			(0.000)	(0.000)			(0.977)
$\Delta\log(Y/Pop)_t$		0.091**			0.031	0.033			-5.394**
		(0.016)			(0.443)	(0.434)			(0.018)
Estimator	SUR-FE	SUR-FE	OLS-FE	OLS-FE	SUR-FE	SUR-FE	SUR-ARDL	SUR-ARDL	SUR-ARDL
$\chi^2(k)$							25.6***	32.7***	31.0***
# Countries	21	21	21	21	21	21	21	21	21
Frequency	10-Year	10-Year	10-Year	10-Year	10-Year	10-Year	10-Year	10-Year	10-Year
Obs.	546	546	462	420	546	546	525	525	525
Est. Per.	1750-2000	1750-2000	1750-1960	1750-1940	1750-2000	1750-2000	1760-2000	1760-2000	1760-2000

Notes. The dependent variable is the general fertility rate, FER; p-values in parentheses. The SUR estimator is used and the parameter estimates are corrected for heteroscedasticity and serial correlation. Time and country fixed effects are included in all regressions. GER is gross enrollment rates at primary and secondary levels; Pat/Pop is patent-intensity; CMR is crude mortality rate; W^{Gap} is gender wage gap; Y/Pop is per capita income. $\chi^2(k)$ is a bounce test for cointegration, distributed as $\chi^2(k)$ under the null hypothesis of no cointegration (where the cointegration vectors are jointly zero), where k is the number of variables included in the cointegration vector. *** = significant at 1%; ** = significant at 5%; * = significant at 10%.

level of $\exp(-0.049/0.006) = 0.00028$, which is about the level of patent-intensity that prevailed over the period 1700-1750.

We exploit these results and perform counterfactual simulations by feeding the period-specific cross-country average patent/population ratio from 1700-2019 into the estimated equation (12). In Figure 8, these elasticities are displayed together with a line at the value of the constant elasticity suggested by the associated linear regression (from column (4) in Table 2). The time-varying patent-elasticity is close to zero before 1750, declines moderately between 1750 and 1830 and descends steeply (i.e., increases steeply in absolute value) over the period 1830 to 1890. It then declines moderately over the period 1890-1950 and levels out thereafter. This path is consistent with UGT to the extent that the steep fertility decline sets in during the 1870s for most countries in our sample, including the technological powerhouses of France, Germany, the UK, and the US. Overall, these results give support to the Galor-Weil model, according to which technological progress initiates the fertility transition when technological progress becomes sufficiently high.

4.5. **Dynamic Effects.** In this sub-section we go beyond the static models we have estimated thus far. We first investigate whether the baseline results are robust to the allowance for long lags in mortality rates and then estimate the ARDL model that allows for dynamic adjustment towards the long-run equilibrium.

To allow for slow adjustment of fertility to the mortality decline that preceded the fertility decline during the 19th century, we add a four-decade lag of CMR to the baseline model in column (6) in Table 6 to check for the possibility that the mortality decline, predominantly induced by the epidemiological transition, preceded the fertility transition. Lags of up to six decades were initially included in the model; however, except for the contemporary effect and the fourth lag, they were statistically insignificant at conventional levels and, consequently, omitted. The coefficients of patent-intensity, wage gap and education are comparable to the baseline regression results. For mortality, the sum of the coefficients of CMR_t and CMR_{t-4} is 0.54, which is not much larger than that of 0.45 in the baseline regression. From these results, it can be concluded that the mortality decline since the mid-19th century has not been sufficiently powerful to significantly influence the net fertility rate and has, therefore, not contributed to the decline in net fertility during the fertility transition.

Finally, we estimate an error-correction representation of the ARDL model (see, e.g., Pesaran et al., 2001), as follows:

$$\begin{aligned}\Delta \log FER_{it} &= \kappa_0 \log FER_{i,t-1} + \kappa_1 \log GER_{i,t-1} + \kappa_2 \log(Pat/Pop)_{i,t-1} + \kappa_3 \log CMR_{i,t-1} \\ &+ \kappa_4 \log W^{Gap}_{i,t-1} + \Delta X_{i,t-1}\xi' + \phi_i + \varphi_t + \epsilon_{4,it}, \qquad (13)\end{aligned}$$

where X is a vector of all the non-deterministic variables in the model including the fertility rate.

The long-run parameter estimates of the ARDL model are shown in columns (7)-(9) in Table 6. The parameter estimates of the first-difference terms are not shown to preserve space. The bound tests for cointegration reject the null hypothesis of no cointegration at any conventional significance level in all three cases, suggesting that a long-run relationship exists between the variables included in the model, where the coefficients of the cointegration vector are zero under the null hypothesis. The long-run coefficients of school enrollment are significantly negative with the magnitudes of -0.15 and -0.16, exclusive of and inclusive confounders. These magnitudes are substantially more negative than the baseline values in Table 2, particularly in the regression in the last column with all confounders included, where the absolute values are twice the size of their baseline counterparts. The coefficients are close to those in the 2SLS regressions; thus, reinforcing the finding of the 2SLS estimates that the coefficients of GER are biased toward zero in the FE-OLS estimates.

In support of UGT, the coefficient of patent intensity is significantly negative in the regressions with no confounders (columns (7) and (8), Table 6) and turns insignificant in the regression when all confounders are included (column (9)). Finally, the coefficient of the crude mortality rate is 0.50, which is close to the estimates in the baseline regressions; again showing that mortality is not likely to have contributed to the decline of net fertility.

5. Conclusion

In this paper, we have tested the mechanism that triggered the fertility transition in the West as predicted by the models by Galor and Weil (2000) and Galor and Moav (2002). To the best of our knowledge, this is the first empirical test of the core mechanism of the canonical Unified Growth Theory (UGT), according to which increasing technological progress initiated and propelled the fertility transition and the take-off of mass education. For this purpose, we compiled a data set for 21 OECD countries over the period 1750-2016, which enables us to capture the fertility transition in its entirety. Rather than using a measure of educational attainment of the population at large, we use enrollment rates in primary and secondary education forwarded ten years in conjunction with contemporary fertility rates in order to closely match the UGT constructs of parental decisions on fertility and child education. We use three alternative measures of skill-biased technological progress: Patent-intensity (patents per capita), the share of net investment in machinery, equipment, and intellectual property products in total GDP, and R&D intensity.

The evidence gives strong support for the UGT of Galor and Weil (2000) and Galor and Moav (2002). The results show that technological progress has a strong positive impact on education and a strong negative effect on fertility – even after we control for other confounders, such as mortality, the gender wage gap, and the level and growth rate of per capita income.

Several tests substantiate that technological progress played a key role in the fertility transition in the OECD countries. First, the coefficients of patent-intensity more than double when school enrollment is excluded from the fertility regression, suggesting that school enrollment is the principal channel through which technological progress influences fertility. Second, genetic-proximity weighted foreign patent-intensity is a significantly stronger instrument for school enrollment in the fertility-regression than compulsory years of schooling and minimum working age. Quantitatively, we find that a 10% increase in patent-intensity is associated with a 2% reduction in the general fertility rate through school enrollments, implying that the increase in patent intensity over the period 1850-1913 contributed to an approximate 35% decline in the fertility rate through education for the average OECD country. Third, while technological progress has tended to suppress fertility since 1750, we find that the technological accelerations and technological progress beyond a certain threshold forcefully suppressed fertility, particularly during the 1850-1913 period. Fourth, we find that the principal results are robust to alternative measures of technological progress, such as R&D intensity and the share of investment in machinery and equipment in total GDP. By contrast, we find that the share of investment in buildings and structures in total GDP does *not* impact negatively on fertility despite being determined by most of the same factors that also drive technological progress.

While the focus has been mainly on the role of technological progress, our results show that the gender wage gap and per capita income have also contributed to the fertility transition. We find that the approximately 50% decline in the gender wage gap over the period 1880–1980 may have contributed up to a 9.5% decline in the fertility rate during the same period, which is consistent with the model of Galor and Weil (1996) in which fertility is influenced by women's opportunity costs of having children relative to the income of the household. Furthermore, we find evidence of a slight but statistically negative influence of per capita income on fertility, where the income effect is approximately twice as big after than before the fertility transition.

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