

INTERGENERATIONAL ASSOCIATIONS AND THE FERTILITY TRANSITION

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Abstract

Evolutionary theorists have long noted that intergenerational transmission in fertility may counteract aggregate fertility decline through a process of natural selection. I study this evolutionary process by estimating how intergenerational associations in fertility vary over the fertility transition and feed back into the level of average fertility. Microdata from 40 developing countries indicate that intergenerational persistence breaks down at the onset of the fertility transition but then strengthens as the transition progresses. These changes are attributable to a reversal of fertility differences by skill, as predicted by economic models of long-run demographic change. As fertility approaches the replacement level, rising intergenerational associations reweight the population to raise aggregate fertility rates, pushing back against aggregate fertility decline. (JEL: J13, O15)

1. Introduction

People tend to look, act, and achieve like their parents, but intergenerational persistence within family lines may break down in times of rapid social change. How do intergenerational linkages evolve during these times, and what consequences do they have for the pace of aggregate change? This paper sheds light on these questions for one of the first intergenerational associations to be estimated, dating to Pearson's early applications of his correlation coefficient (Pearson, Lee, and Bramley-Moore 1899): that involving the fertility of mothers and daughters.

In the study of intergenerational associations, fertility stands out relative to other outcomes because, from an evolutionary perspective, it is both a phenotype and a direct force for selection (Cavalli-Sforza and Feldman 1981; Boyd and Richerson 1988). On top of any intergenerational transmission, lineages with higher fertility

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in one generation comprise a larger share of the next. For this reason, evolutionary biologists have puzzled over how a low-fertility strategy came to dominate recent human demographic history. In their canonical text on cultural evolutionary theory, Cavalli-Sforza and Feldman point out that to sustain the demographic transition, the low-fertility strategy must horizontally diffuse fast enough to outpace natural selection from the “continued vertical transmission of the older ‘natural’ fertility habit” (1981, p. 189).¹

This race between innovation and selection may help shed light on aggregate fertility dynamics during the demographic transition, yet it has received surprisingly little attention from economists and demographers.² In demography, a large empirical literature estimates intergenerational fertility associations (mostly in Western populations) but does not draw clear-cut links to aggregate change.³ In economics, empirical research on intergenerational associations in a range of outcomes has prioritized disentangling their causal mechanisms (Currie and Moretti 2003; Black, Devereux, and Salvanes 2005; Sacerdote 2007; Björklund, Lindahl, and Plug 2006), with less interest in how they change with and shape aggregate processes that span generations. With an eye to these issues, I use microdata from 40 developing countries to estimate intergenerational fertility associations at different stages of the demographic transition and assess how they affect the pace of aggregate change across generations.

The paper puts forward two core hypotheses, one coming from the evolutionary model of the fertility transition and one refining it. The first is that a positive intergenerational association in fertility pushes up average fertility, as it raises the population share of higher-fertility women. The second is that the intergenerational association is positive before and after the fertility transition but breaks down at its onset, when the formerly highest-fertility lineages are first to adopt a low-fertility strategy. That is to say, the onset of the fertility transition ruptures intergenerational persistence in relative fertility. Combining the first and second hypotheses, the weakening and subsequent strengthening of the intergenerational association weight the population in a way that first facilitates and then hinders aggregate fertility decline.

The hypothesized dynamics of the intergenerational association are driven by a reversal of fertility differences by skill. Higher-skill parents have more children than their counterparts before the fertility transition, but at its onset, their fertility falls below

1. Summarizing these ideas for economists, Bergstrom raises the “disquieting possibility” that “the low birth rates currently observed in the West do not represent long-run equilibrium” (Bergstrom 1995, p. 1912).

2. In demography, Murphy and Wang (2003) and Kolk, Cownden, and Enquist (2014) investigate how intergenerational fertility associations influence aggregate fertility rates, but only in the context of stylized microsimulation models. In economics, Galor and Moav (2002), Galor and Michalopoulos (2012), Galor and Ozak (2016), and Galor and Klemp (2019) consider how differential reproductive success has influenced human evolution, but without direct attention to how intergenerational associations in demographic outcomes affect the aggregate time series of the same outcomes. An exception is Galor and Klemp (2019), who discuss how the effect of fecundity on long-run reproductive success leads to natural selection.

3. Seminal contributions include Huestis and Maxwell (1932), Duncan et al. (1965), Ben-Porath (1975), Wise and Condie (1975), Anderton et al. (1987), Kahn and Anderson (1992), and Axinn, Clarkberg, and Thornton (1994).

that of the lower skilled. This reversal appeared as a theoretical prediction in Galor and Moav's (2002) model of evolution and economic growth, and recent empirical studies have confirmed it in a wide range of historical and contemporary contexts (Skirrbek 2008; Bengtsson and Dribe 2014; Clark and Cummins 2015; Vogl 2016).⁴ When the skill–fertility relationship is stable across generations, it promotes the association of parents' and children's fertility. However, at the onset of the transition, the association diminishes and may even become negative: higher-skill parents bear more children, but their higher-skill children grow up to have low relative fertility. This process contrasts the original cultural evolutionary model of the fertility transition, in which all lineages start with “natural” fertility and only some initially adopt the “small family ideal” (Cavalli-Sforza and Feldman 1981, p. 186).

To shed light on this difference, the paper starts by examining how economic theory adds insight to an evolutionary-demographic model of the intergenerational fertility association. After deriving basic results about how intergenerational associations shape average fertility, I examine what each theoretical framework implies for the dynamics of average fertility in a stylized two-group population. In the evolutionary-demographic model, one group's fertility falls below the other's at transition onset, leading to selection against the first. However, the model does not speak to how fertility varies before the transition, nor to why fertility declines more in the first group. Economic models of long-run fertility change propose answers to both questions and also predict slightly different population dynamics after transition onset.

Two variants of these long-run models are relevant for understanding differential fertility and its reversal, both of them involving parental choice over the quantity and quality of children. In the first, Galor and Moav (2002) analyze how heterogeneity in preferences over quality and quantity interacts with a subsistence constraint for parental consumption. When the constraint binds, quality-preferring families have more children due to their higher incomes, but after productivity growth pushes the economy beyond the constraint, quality-preferring families opt for fewer children than quantity-preferring families. In the second, de la Croix (2013) and Vogl (2016) analyze how heterogeneity in the costs of quality and quantity interacts with a quality endowment. When incomes are low or the costs of quality high, families forego quality investment, shutting down the quality–quantity tradeoff so that higher-skill parents have more children due to their higher incomes. But as incomes rise and the costs of quality fall, families exit this corner solution, and higher-skill parents choose fewer children than lower-skill parents if they have a comparative advantage in producing quality. Past research (Vogl 2016) finds that the reversal of differential fertility in postwar developing countries was more consistent with the corner solution mechanism, so the theoretical framework in what follows focuses on that mechanism.⁵ In that setup, rising

4. The empirical studies report fertility differences by education, occupation, income, or wealth, with qualitatively similar results across measures. Fisher (1930) and Becker (1981) also discuss the reversal of differential fertility, albeit with limited evidence of the pretransition pattern.

5. Although this evidence suggests the corner solution mechanism, it does not speak to the deep determinants of skill heterogeneity, which may indeed include preferences (as in Galor and Moav 2002) or fecundity (as in Galor and Klemp 2019).

living standards or returns to human capital investment trigger an intergenerational cleavage in relative fertility. Compositional dynamics are qualitatively similar to the basic evolutionary model, but the economic model predicts more a sustained process of fertility decline because human capital rises gradually.

The paper sheds light on these theoretical issues by estimating mother–daughter fertility associations in birth cohorts covering the second half of the 20th century. In recent cohorts, women with more siblings bear more children in adulthood, but in earlier cohorts, the association is significantly weaker and is even significantly negative in many cases: women with more siblings bear *fewer* children in adulthood.⁶ This finding highlights how the fertility transition reverses relative fertility across lineages within a single generation. Fertility decline is not uniform; it reaches the most fertile lineages first. For a behavior often thought to be determined by long-standing culture, the results highlight how rapid changes in the economic, cultural, and institutional environment can influence not just the overall level of fertility but its distribution.⁷ As predicted by the theoretical framework, shifting education–family size relationships play an important role. In all cohorts, a woman’s own fertility declines with education, consistent with the post-transition pattern. In recent cohorts, more educated women also have fewer siblings, raising the intergenerational association of fertility, but in earlier cohorts, more educated women have *more* siblings, weakening it. Both within and across countries, the intergenerational association is more positive when the sibsize–education relationship is more negative.

When the intergenerational association strengthens, the population share of high-fertility parents rises, pushing back against aggregate fertility decline. To quantify this phenomenon, the paper estimates the *composition effect* of differential fertility, which captures how mean fertility differs from what it would have been if women were represented in the population as if their parents all had the same number of children.⁸ Estimated at the country-cohort level, the composition effect becomes significantly stronger as fertility declines; well into the fertility transition, heterogeneity in the number of children across mothers in one generation compositionally raises the mean fertility of their daughters by 4% on average. To link these cohort analyses with the evolution of total fertility rates (TFR), the paper also carries out a complementary analysis of period fertility, aggregating over the cross-sectional age distribution in a given year. Here again, the composition effect on TFR becomes significantly stronger

6. Unfortunately, the cohorts in the data do not go far back enough to establish a positive pretransition intergenerational association, only a weak to negative association at transition onset and a subsequent strengthening.

7. For insight into the interplay between culture and the economic environment, see Fernández and Fogli (2009), Chabé-Ferret (2016), de la Croix and Perrin (2018), Spalao and Wacziarg (2019), and Daudin, Franck, and Rapoport (2019).

8. The composition effect of differential fertility is similar to population momentum (Keyfitz 1971). Population momentum stems from the gradual evolution of the population age structure following a change in age-specific fertility rates. Analogously, one can view the composition effect as reflecting the gradual evolution of lineages’ population shares following a change in their relative fertility rates.

as TFR declines. In populations with TFRs less than 3, differential fertility raises TFR by 4% on average.

These findings demonstrate a role for heterogeneity in driving aggregate fertility dynamics. In this sense, they relate to the economics literature on how microlevel demographic phenomena like differential fertility and assortative mating aggregate up to the population or economy (Lam 1986; Kremer 1997; Fernandez and Rogerson 2001; de la Croix and Doepke 2003). That literature focuses largely on aggregating skill or income across households, whereas this paper shifts attention toward fertility behavior. The paper also expands on classic demographic research relating the average family sizes of women and children. Preston (1976) points out that because children from larger families are over-represented in the population, the average family size of children (i.e., sibship size) is generally larger than the average family size of women (i.e., fertility). In a hypothesis recently confirmed by Lam and Marteleto (2013), Preston posits that this difference shifts slowly during the demographic transition, so that average sibship size falls more slowly than average fertility. Just as in this paper, differential fertility reweights the population to slow the pace of aggregate demographic change experienced by the next generation. Both lines of research highlight the value of considering how the cross-section interacts with the aggregate time series.

Additionally, the results add to a large body of research, spanning the social sciences, on intergenerational associations in a range of outcomes, behaviors, and traits. Especially relevant is the recent economics literature that studies how intergenerational associations vary across space and over time. Much of this literature focuses on intergenerational earnings mobility, investigating its variation across countries (Björklund and Jäntti 1997; Corak 2013) and across subnational areas within a country (Chetty et al. 2014). International comparisons are also available for associations in other outcomes, including educational attainment (Hertz et al. 2007; Chevalier, Denny, and McMahon 2009) and health (Bhalotra and Rawlings 2013). Closest to this paper is Murphy's (2012) analysis of intergenerational fertility associations in 46 developing countries. Murphy estimates these associations to be weaker than in developed countries (Murphy 2009) but also finds some evidence of a u-shape in the level of development. This paper extends Murphy's analysis to shed light on changes in the associations over time within countries, their determinants, and their consequences for aggregate fertility. In another closely related analysis, Galor and Klemp (2019) estimate the effect of fecundity on long-run reproductive success in preindustrial Quebec, finding that settlers with moderate fecundity had the most descendants after several generations. There as here, interactions between child quantity and quality are key to understanding intergenerational relationships in reproductive outcomes.

2. Conceptual Framework

This section derives how intergenerational fertility associations aggregate up to the population level and explores their implications for the dynamics of average fertility across generations, with attention to how evolutionary-demographic and economic

frameworks differ in their mechanisms and predictions. The evolutionary-demographic framework takes fertility heterogeneity and its transmission as exogenous, whereas the economic framework endogenizes fertility and child investment.

2.1. Evolutionary-Demographic Framework

To simplify the exposition, assume a one-sex population; the empirical work will extend the analysis to two sexes. Let n_{ijt} be the fertility of individual i from sibship j in generation t , where a sibship is defined as all individuals with the same parent. Let s_{jt} be the number of siblings in sibship jt , and let $\bar{n}_{jt} \equiv \sum_i n_{ijt}/s_{jt}$ be their mean fertility. Given the notation, the parent of sibship jt has $s_{jt}\bar{n}_{jt}$ grandchildren. The paper is interested in two phenomena: the transmission of fertility heterogeneity across generations and the reweighting of the population due to fertility heterogeneity.

2.1.1. Intergenerational Association. Define the *intergenerational fertility association*, β_t , as the slope coefficient from the linear projection of n_{ijt} on s_{jt} :

$$n_{ijt} = \alpha_t + \beta_t s_{jt} + u_{ijt}. \quad (1)$$

The slope coefficient reflects an intergenerational association because the number of siblings in an individual's sibship is the same as the fertility of the individual's mother. In the language of cultural-evolutionary theory, β_t reflects the vertical (parent-to-child) transmission of relative fertility. Cavalli-Sforza and Feldman (1981) posit that fertility starts at a "natural" level that does not vary systematically across lineages, that a subset of lineages adopt a low-fertility strategy at transition onset, and that the low-fertility strategy is intergenerationally persistent. Their theory implies that $\alpha_t > 0$ and $\beta_t = 0$ before the transition, and that onset reduces α_t while raising β_t . In contrast, I hypothesize that β_t is positive before and after the onset of the fertility transition but weak to negative at onset.

Intergenerational associations in fertility may arise due to (i) the causal effects of family size, (ii) the genetic heritability of fecundity and fertility preferences, (iii) cultural influences on fertility behavior, and (iv) linkages across generations in the socioeconomic determinants of fertility. Let X_{ijt} be a vector containing the mediators in (iii)–(iv). If the conditional expectation of n_{ijt} is linear in s_{jt} , then we can write the intergenerational association as

$$\beta_t = \frac{dE[n_{ijt}|s_{jt}]}{ds_{jt}} = \frac{\partial E[n_{ijt}|s_{jt}, X_{ijt}]}{\partial s_{jt}} + \frac{\partial E[n_{ijt}|s_{jt}, X_{ijt}]}{\partial X_{ijt}} \cdot \frac{dE[X_{ijt}|s_{jt}]}{ds_{jt}}. \quad (2)$$

The first component, $\partial E[n|s, X]/\partial s$, represents any intergenerational transmission that is not mediated by X_{ijt} , including genetics, preference transmission, the causal effect of sibship size.⁹ The second and third components make up the part of the association that

9. Regarding genetics, age at menarche, age at menopause, and menstrual regularity are heritable (Van den Akker et al. 1987; Treloar and Martin 1990). Also, Barban et al. (2016) identify genetic loci associated

is mediated by X_{ijt} , with $\partial E[n|s, X]/\partial X$ reflecting the association of X_{ijt} with fertility, and $dE[X|s]/ds$ reflecting the association of sibship size with X_{ijt} . The hypothesized dynamics of β_t reflect staggered changes in $\partial E[n|s, X]/\partial X$ and $dE[X|s]/ds$ for the case in which X_{ijt} represents skill. Before the onset of the fertility transition, richer and more educated parents have more children than their less fortunate counterparts, and children with many siblings obtain more education than children with few; afterward, both patterns are reversed. Within either regime, $\partial E[n|s, X]/\partial X$ and $dE[X|s]/ds$ have the same sign, increasing the intergenerational association of fertility. But for the last generation born under the pretransition pattern, a larger sibship is associated with more education, whereas more education is associated with fewer children. As a result, the product $\partial E[n|s, X]/\partial X \cdot dE[X|s]/ds$ turns negative, putting downward pressure on the intergenerational association and making it negative if $\partial E[n|N, s]/\partial s$ is small.

2.1.2. Composition Effect. Define the composition effect of differential fertility in generation $t - 1$ on average fertility in generation t , Δ_t , as the difference between the average of n_{ijt} across individuals and the average of \bar{n}_{jt} across sibships:

$$\Delta_t = E[n_{ijt}] - E[\bar{n}_{jt}] = E\left[\left(\frac{s_{jt}}{E[s_{jt}]} - 1\right)\bar{n}_{jt}\right]. \quad (3)$$

The second equality follows because $E[n_{ijt}] = E[(s_{jt}/E[s_{jt}])\bar{n}_{jt}]$. The distribution of \bar{n}_{jt} is reweighted by the factor $s_{jt}/E[s_{jt}]$ to give more weight to individuals from larger sibships, reflecting the changing composition of the population from $t - 1$ to t . If individuals from larger sibships have more children themselves, then the added weight given to larger sibships raises average fertility, so that $\Delta_t > 0$. In this case, fertility heterogeneity in generation $t - 1$ raises average fertility in generation t .

How do β_t and Δ_t relate? If the conditional expectation of n_{ijt} is linear in s_{jt} , then

$$\Delta_t = \beta_t \frac{V[s_{jt}]}{E[s_{jt}]}. \quad (4)$$

Online Appendix A.1 provides a derivation. One component measures similarity in the reproductive behavior of parents and children, whereas the other measures the relative spread of the fertility distribution among parents. Because the second component is always positive, the composition effect is negative if and only if the intergenerational association is negative. In absolute value, the composition effect is larger when the intergenerational association is larger or when the variance of sibship size is larger relative to its mean.¹⁰ Thus, the hypothesized dynamics of β_t imply that Δ_t is positive before and after the onset of the fertility transition but weak to negative

with age at first birth and children ever born. Regarding preferences, gender attitudes are intergenerationally correlated (Dhar, Jain, and Jayachandran 2019).

10. The variance-to-mean ratio $V[s_{jt}]/E[s_{jt}]$ also appears in Preston's (1976) formula for the difference between the average family size of children and the average family size of women. Both there and here, it implies that the aggregate implications of heterogeneous sibship size are larger when sibship size is more dispersed relative to its mean.

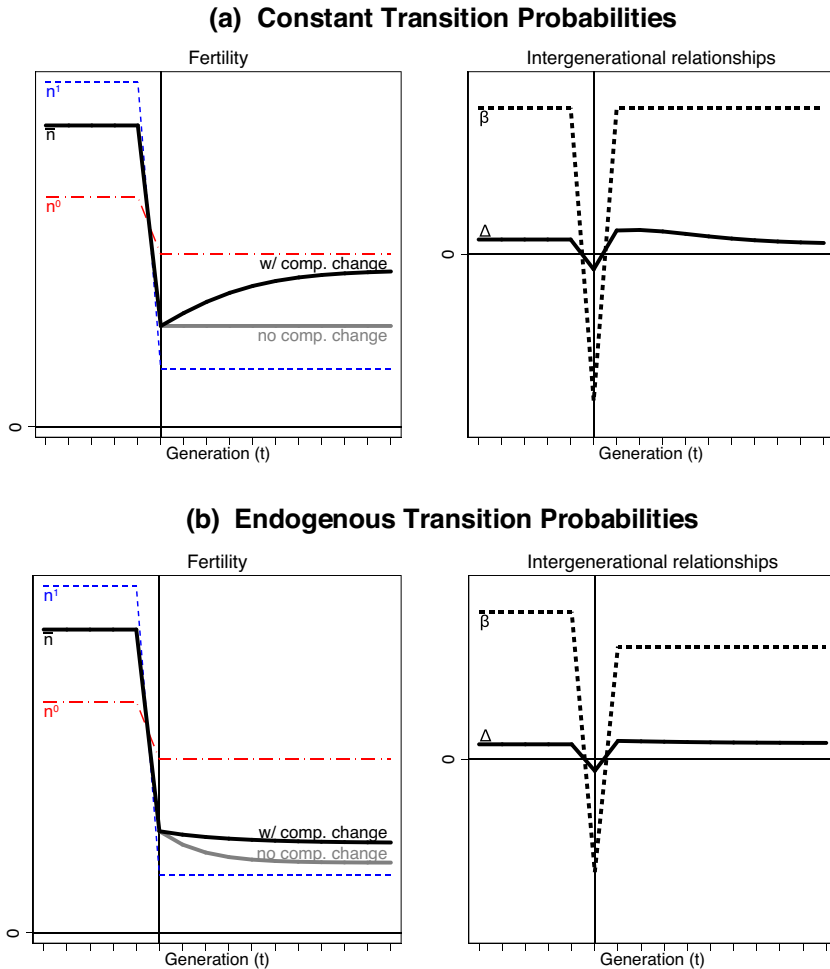


FIGURE 1. Fertility dynamics in a two-type population. n^1 and n^0 represent the fertility of types 1 and 0; \bar{n} is average fertility in the population; β is the intergenerational fertility association; Δ is the composition effect.

at onset. As Δ_t regains strength after onset, it pushes back against aggregate fertility decline.

2.1.3. Aggregate Fertility Dynamics. To demonstrate these aggregate implications, panel (a) of Figure 1 plots fertility and intergenerational relationships following the onset of a prototypical fertility transition in a population with two types of adults, indexed 0 and 1. In the evolutionary-demographic model, we define types by their behavior and assume exogenous probabilities that children keep their parents' types; in the economic model that follows, we will define types by their resources or preferences, with behavior and transition probabilities arising endogenously. Type 1

fertility (n_t^1) is initially higher than type 0 fertility (n_t^0), but type 1 adopts new fertility strategies more intensively than type 0. Children with type 1 parents remain in type 1 with probability π^1 , and children with type 0 parents switch to type 1 with probability π^0 , where $\pi^1 > \pi^0$.

The population starts in steady state, so that the type 1 share of the adult population is stable, as is average fertility \bar{n}_t . In the sixth generation (characterized by the vertical line), fertility permanently declines for both types, but more for type 1 than for type 0. Because n_t^1 and n_t^0 are stable before the reversal and $\pi^1 > \pi^0$,

$$\beta_t = (\pi^1 - \pi^0) (n_t^1 - n_t^0) / (n_{t-1}^1 - n_{t-1}^0)$$

is initially positive, and by equation (4) so is Δ_t . In the generation of transition onset, both become negative: individuals born into larger families have fewer children than those born into smaller families.¹¹ Afterward, n_t^1 and n_t^0 resume their stability, making β_t and Δ_t positive again.

What do these composition effects imply for the evolution of average fertility after the fertility transition? Panel (a) plots two averages, one that does not update the composition of the population to reflect changes in differential fertility (gray), and one that does (black). Because it does not incorporate compositional changes, the gray series is flat after the transition. In contrast, the black series gradually increases after the initial decline, as the composition of the population adjusts to a new steady state with a higher share of low-skill adults. The gradual adjustment of average fertility reflects the cumulation of composition effects.

This stylized example departs from Cavalli-Sforza and Feldman's (1981) assumption that pretransition fertilities are equal. With equal pretransition fertilities, composition effects would still rise after onset, but the decline of average fertility at onset would depend on the initial population composition of types, rather than the steady-state composition that arises from unequal pretransition fertilities. The unequal fertilities assumption here is attractive because it offers a prediction that one can verify in the data: Δ_t may be negative at transition onset. However, it begs the questions of why n_t^1 exceeds n_t^0 before the transition, and why this pattern flips.

2.2. Economic Framework

What forces reverse differential fertility? Economic models incorporating long-run growth, the demographic transition, and cross-sectional heterogeneity provide a useful framework for answering these questions (Galor and Moav 2002; Hazan and Berdugo 2002; de la Croix and Doepke 2003; Moav 2005; de la Croix 2013). This section presents a stylized version of these models to highlight economic mechanisms underlying the reversal of differential fertility and to understand how predicted population dynamics differ from those of the evolutionary-demographic framework.

11. As discussed previously, this stark intergenerational cleavage may be muted in the data by other sources of intergenerational transmission, so that β_t and Δ_t shrink but do not necessarily turn negative.

2.2.1. Model. The two-type case from Section 2.1 will continue to be expositorially convenient. Types 0 and 1 are now low- and high skill, receiving wage rates $w_t^1 > w_t^0$ for a unit of time worked. Adults maximize a log-linear utility function over own consumption c_{ijt} , the number of children n_{ijt} , and each child's probability of becoming a high-skilled adult π_{ijt} :

$$U = \gamma \log(c_{ijt}) + (1 - \gamma) \log(n_{ijt}\pi_{ijt}) \quad (5)$$

$\gamma \in (0, 1)$ reflects the importance of consumption relative to the combined quality and quantity of children. Child quality, as represented by the high-skill probability, is determined by education spending per child e_{ijt} , according to an increasing, concave, and twice differentiable function $\pi(e_{ijt})$, with $\pi(0) > 0$. Apart from education spending, each child costs $\tau \in (0, 1)$ units of time and $\kappa > 0$ goods. Denote by n_t^X and e_t^X the solutions for parents of type X in generation t , and denote by π_t^X the associated probability of that their children become high-skilled adults.

Online Appendix A.2 establishes two comparative statics that are key to understanding intergenerational fertility associations. First, educational investment weakly increases with the wage. Second, if the elasticity of $\pi(\cdot)$ rises with e_{ijt} , and κ is sufficiently small, fertility has a hump-shaped relationship with the wage.¹² Sufficiently low-wage parents choose a corner solution with no education spending, which shuts down the quality–quantity tradeoff, so that fertility rises with the wage on the margin. Sufficiently high-wage parents choose an interior solution for education spending, which reinstates the quality–quantity tradeoff and (under the stated assumptions) leads to a negative relationship between the wage and fertility. If fertility is initially higher for the high-skill group, then sufficiently large, permanent increases in wages or the return to education expenditure (as characterized by the logarithmic derivative of $\pi(\cdot)$) permanently reverse the fertility differential.¹³ Because the fertility differential has the same sign in all generations before this transition and in all generations after it, the intergenerational association

$$\beta_t = (\pi_{t-1}^1 - \pi_{t-1}^0)(n_t^1 - n_t^0)/(n_{t-1}^1 - n_{t-1}^0)$$

is negative in the transition generation with $n_{t-1}^0 < n_{t-1}^1$ and $n_t^0 > n_t^1$ but positive in all other generations.

12. Jones, Schoonbroodt, and Tertilt (2010) discuss the consequence of a rising elasticity of $\pi(\cdot)$ for the case with $\kappa = 0$. A common functional form is $\pi(e_{ijt}) = (1 + e_{ijt})^\theta$, $\theta \in (0, 1)$, which exhibits a rising elasticity. When the assumptions about $\pi(\cdot)$ and κ do not hold, the declining portion of the hump-shape disappears, so that fertility (weakly) increases with the wage: inconsistent with widespread empirical patterns.

13. Due to the hump-shape, an increase in wage inequality has an ambiguous effect on the fertility differential. One can capture child mortality by dividing the quantity costs of children by the survival rate, but it has an ambiguous effect on the fertility differential in this setup. Consistent with this ambiguity, the empirical results are similar whether one counts all children ever born or only surviving children. The empirical results also show no relationship between infant mortality rates and intergenerational fertility associations.

2.2.2. Aggregate Fertility Dynamics. Panel (b) of Figure 1 updates panel (a) to incorporate the predictions of the microfounded model. Panel (a) simulated a decline and reversal of n_t^H and n_t^L holding π_t^H and π_t^L fixed. In the microfounded model, the forces that lead to these changes in fertility (e.g., rising wages or returns to education spending) also increase π_t^X for one or both skill groups.

As such, panel (b) plots aggregate fertility dynamics when π_t^H and π_t^L rise as n_t^H and n_t^L fall. The key difference from panel (a) is that the increase in π_t^X gradually raises the high-skill share of the population, which in turn decreases average fertility. The gray series, which does not update the composition of the population to reflect changes in differential fertility, now trends downward after the initial decline. The black series, which does update the composition of the population, may rise or fall but remains strictly higher than the gray series. Endogenizing π_t^X influences the predicted level of average fertility, but it does not qualitatively alter the effect of differential fertility.

2.2.3. Alternative Models. The previous setup follows de la Croix and Doepke (2003), Moav (2005), de la Croix (2013), and Vogl (2016), in that it explains differential fertility and its evolution by varying child costs across parental skill levels. Quality costs money but not time, whereas quantity costs both, and high-skill parents have more money but more expensive time. The paper does not seek to disentangle mechanisms but instead to empirically establish how intergenerational associations change with and feed back into the fertility transition, so the model serves to show how the empirical results arise in a standard theoretical framework.

However, existing empirical evidence supports the setup here and provides somewhat less backing for alternative explanations of the reversal of differential fertility. In a prominent alternative, Galor and Moav (2002) assume a parental subsistence consumption constraint and heterogeneous preferences over quality and quantity.¹⁴ Their setup has similar implications for intergenerational associations and aggregate fertility dynamics, but the empirical record for postwar developing countries is more consistent with a corner solution in quality investment than with a subsistence consumption constraint. In Vogl (2016), I find that the hump-shaped relationship between economic status and fertility has changed, with the peak shifting to the left over time. Such a shift is consistent with poorer and poorer parents exiting the corner solution over time, but it is not easily reconciled with a subsistence consumption constraint. At the same time, a corner solution does not rule out preference heterogeneity. If preference heterogeneity played a role, then the compositional dynamics discussed previously would be driven by changes in the distribution of preferences in addition to the distribution of skill.

Other candidate drivers of changing differential fertility include heterogeneity in child investment returns or women's work. If high-skill parents had higher returns to

14. Specifically, Galor and Moav assume $U = \gamma \log(c_{ijt}) + (1 - \gamma)\{\log(n_{ijt}) + \lambda \log(\pi_{ijt})\}$, with heterogeneity in λ . Equation (5) sets $\lambda = 1$ because this parameter is not essential to the previous mechanism.

investing in children instead of lower costs, the basic mechanisms would not change, and similar results would obtain. If the costs of quantity for high-skill parents rose because of increases in women's labor market productivity as in Galor and Weil (1996), the theoretical mechanisms would indeed change, but the evidence again suggests that the reversal of differential fertility has other drivers. In Vogl (2016), I find that changes in differential fertility are not associated with increases in female labor force participation or changes in the sectoral composition of the economy.

3. Data on the Fertility of Mothers and Daughters

To link mothers' and daughters' fertilities, I draw on data from the Demographic and Health Surveys, a collection of nationally representative samples of women of childbearing age (generally 15–49). Two survey modules are key for the analysis. The fertility history module asks women to list all of their own children ever born, whereas the sibling history module asks women to list all of their siblings ever born to their mothers, both with details like birthdates and survival. Combined, these two lists allow one to retrospectively track fertility outcomes in a lineage over two generations. The retrospective nature of both survey modules makes them subject to misreporting of dates and omissions of births (Schoumaker 2014), but these errors may not be correlated across modules. Previous analyses of intergenerational fertility correlations using DHS data have argued that the data are of high quality (Murphy 2012).

Although the design of the DHS allows for comparisons across surveys and countries, questionnaires and sampling methods occasionally differ. Surveys must meet two criteria for inclusion in the study sample. First, they must sample all women, not only ever-married women, to avoid sample selection on an outcome closely related to fertility.¹⁵ Second, they must include information on the survival of both offspring and siblings, to allow analysis of both ever-born and surviving fertility. Based on these criteria, the paper uses 82 surveys in 40 African, Asian, Caribbean, Latin American, and Pacific countries (see Online Appendix Table A.1 for a list of countries and survey years).¹⁶ Together, these surveys provide data on sibship size and fertility for 966,498 women aged 15–49.

As its main unit of analysis, the analysis focuses on birth cohorts, estimating intergenerational associations and composition effects among women born in the same country and the same 5-year interval. Because this approach generates parameter estimates for many cells per country, it allows a rich analysis of changes in associations and composition effects within a country over time. The ideal unit would be a generation (all women born to the same group of mothers), but DHS data do not allow estimation of generational statistics.

15. The one exception to this rule is the 1996 Nepal DHS, which surveyed only ever-married women. Because 98% of Nepalese women over 30 in that year were ever-married, I include data from that survey on women over 30.

16. Two additional surveys, the 1989 Bolivia DHS and the 1999 Nigeria DHS, meet the sample inclusion criteria but are omitted due to irregularities in the sibling history data.

Analyses of the intergenerational association and the composition effect involve two steps: first, estimating parameters for each country-cohort cell, and second, documenting patterns across (rather than within) cells. In the first step, I use sampling weights provided by the DHS but rescale them to maximize efficiency with multiple surveys per country.¹⁷ In the second step, analyses are unweighted to ensure representativeness. For precision, I drop cells smaller than 250 women, the 5th percentile of the cell size distribution.

In an extension to the cohort analysis, I quantify implications for the total fertility rate (TFR), a period measure of fertility that reflects the expected number of children for a woman who experiences current age-specific fertility rates throughout her lifetime. The unit of analysis is a country-year, so each survey generates a single estimate, and no weight rescaling is necessary.

Many parts of the analysis focus on relationships between estimated parameters, which are based on the same underlying sample. For conservative statistical inference, I bootstrap all such analyses in a two-step procedure. The first step randomly draws primary sampling units within each survey, whereas the second step randomly draws countries.¹⁸ I do not otherwise correct for estimation error in the cell-level parameter estimates; earlier work on the same data set (Vogl 2016) found that Fuller's (1987) error correction procedure did not meaningfully change the results.

4. Intergenerational Fertility Associations

This section estimates intergenerational fertility associations at the country-cohort level and studies how they evolve. It reports results for both ever-born fertility, which is more relevant for associations in fertility behavior, and surviving fertility, which is more relevant for associations in fertility outcomes. Surviving fertility also influences population composition and may be less subject to recall bias. Either measure may be relevant for the demand for children, depending on parents' ability to target the number of surviving offspring subject to mortality risk.

4.1. Methods

I estimate intergenerational associations using an ordinary least squares (OLS) model relating a woman's fertility outcome at a specific age to her sibship size. For woman i from country c and 5-year birth cohort t :

$$n_{ict}^a = \alpha_{ct}^a + \beta_{ct}^a s_{ict} + u_{ict}^a, \quad (6)$$

17. If a country-cohort cell includes data from surveys $k = 1, \dots, K$, each with N_k observations, then the weights from survey k are rescaled to sum to $N_k / \sum_k N_k$. This approach weights surveys in proportion to their contribution to the cell.

18. Unless otherwise noted, I compute analytical standard errors (clustered by primary sampling unit) for the cell-level statistics themselves. Only the analyses relating estimated cell-level parameters are bootstrapped.

where n_{ict}^a is cumulative fertility at age a , and s_{ict} is sibship size. β_{ct}^a is country-cohort ct 's intergenerational fertility association at age a , capturing *all* mechanisms linking a mother's fertility with her daughter's.

The choice of a poses a methodological tradeoff. The DHS interviews most respondents midway through their childbearing years, so the analysis must consider cumulative fertility before the end of reproductive age. An earlier a allows for a larger sample and coverage of later birth cohorts, whereas a later a covers more of the reproductive lifespan. To deal with this trade-off, I follow research on intergenerational income mobility, where similar issues arise (Haider and Solon 2006).¹⁹ Chetty et al. (2014) choose the age at which the intergenerational income association becomes stable for the rest of the lifecycle. If fertility gaps are concentrated early in the reproductive lifespan, then one can take a similar approach to analyzing intergenerational fertility associations. To find the earliest age a for which β_{ct}^a approximates the completed fertility association, I draw on the full fertility histories of women at least 45 years old to estimate β_{ct}^a at ages 20, 25, 30, 35, 40, and 45. I then regress each cohort's age-45 association on its association at an earlier age. The solid curves in Figure 2 display the results, indicating that intergenerational associations at earlier ages are informative about the association for completed fertility (as measured at age 45). From age 25 on, all estimated slopes are close to 1, but at age 20, the estimated slope for surviving fertility is substantially below 1.²⁰ These results suggest that fertility differences by childhood family size are concentrated at early ages, so that the intergenerational association at age 25 can serve as a proxy for the intergenerational association in completed fertility. If gaps in fertility risk were constant over the reproductive lifespan, then one could estimate a Poisson model, and the results would appealingly not depend on the age at measurement. The solid curves in Figure 2 suggest that these gaps are not constant, but to shed direct light on the issue, the dashed curves in Figure 2 redo the exercise using Poisson instead of OLS estimates of the intergenerational association. Unlike OLS, the Poisson estimates at earlier ages are poor proxies for the intergenerational association in completed fertility. Given these results, the cohort analysis relies on OLS models of the intergenerational association, using cumulative fertility at age 25 as the outcome.

Motivated by equation (2), one can decompose the intergenerational fertility association into its driving forces: (i) the association of sibship size and fertility, conditional on human capital; (ii) the association of human capital and fertility, conditional on sibship size; and (iii) the association of sibship size and human capital. Two equations summarize these three derivatives. The first expresses fertility outcomes as a function of sibship size and education (X_{ict}):

$$n_{ict}^a = A_{ct}^a + B_{ct}^a s_{ict} + \Gamma_{ct}^a X_{ict} + U_{ict}^a, \quad (7)$$

19. Since age-earnings profiles are steeper for individuals with high lifetime earnings, early measurement of the child's income can bias estimates of the parent-child association downward. This lifecycle bias is analogous to the problem that arises here, except that the dependent variable is a flow (income) rather than a stock (cumulative fertility).

20. From age 25 on, all estimated slopes are significantly different from 0 and not significantly different from 1; at age 20, the estimated slope for surviving fertility is not significantly different from zero.

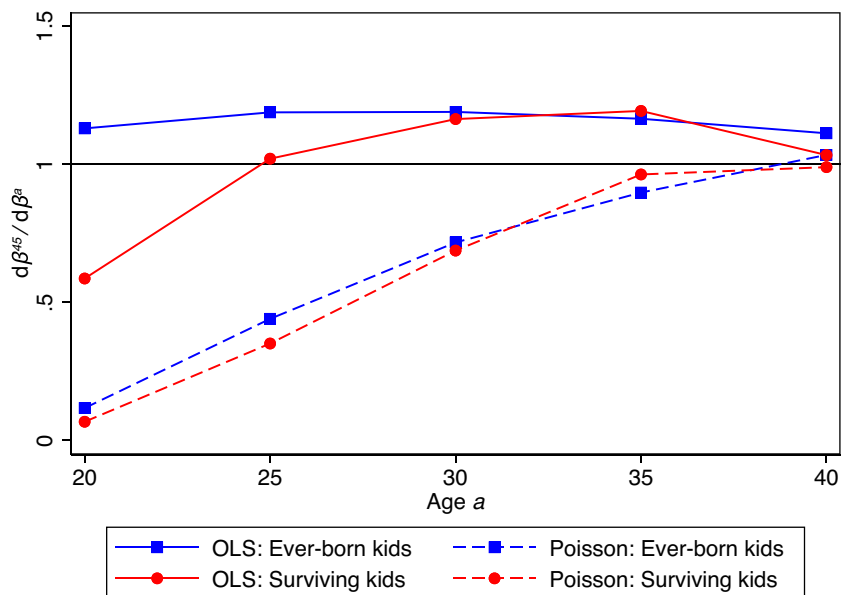


FIGURE 2. Specification choices. For both OLS and Poisson models of the intergenerational fertility association, the figure seeks the earliest age at fertility measurement for which the association approximates the intergenerational association in completed fertility. Each point represents the coefficient from a regression of the intergenerational association at age 45 on the intergenerational association at the specified earlier age. The sample includes 75,062 women from 95 country-cohort cells with at least 250 women over age 45.

whereas the second expresses education as a function of sibship size:

$$X_{ict} = \psi_{ct} + \varphi_{ct}s_{ict} + v_{ict}. \tag{8}$$

In the language Goldberger (1991) uses to characterize omitted variable bias, equation (6) is a “short” regression, whereas equations (7) and (8) are the corresponding “long” and “auxiliary” regressions. B_{ct}^a is the net intergenerational transmission term discussed in Section 2.4, accounting for factors outside the theoretical framework. Γ_{ct}^a is the skill–fertility association, representing differential fertility in the current generation, whereas φ_{ct} is the sibsize–skill association, reflecting differential fertility in the last generation. By equation (2), the cohort coefficients are related by the identity $\beta_{ct}^a = B_{ct}^a + \varphi_{ct}\Gamma_{ct}^a$, which confirms that β_{ct}^a is smaller when Γ_{ct}^a and φ_{ct} are of opposite sign.

4.2. Results

The analysis of intergenerational fertility associations proceeds in six steps. To build intuition for the full-sample results, I first present a case study of Bolivia, which has data covering birth cohorts from the mid-1940s to the mid-1980s, between which the country underwent a marked reversal of differential fertility. Next, I describe the

distribution of parameter estimates in the full sample, followed by an exploration of how they change across cohorts, how they relate to each other, and how they relate to other demographic processes like marriage. Finally, I regress the fertility associations on economic aggregates in early life and early adulthood to understand the drivers of the observed changes.

4.2.1. Bolivian Case Study. The case study of Bolivia appears in Table 1. To reduce the number of results to report, the case study uses decadal birth cohorts instead of the 5-year cohorts of the main analysis. For each decade of birth from 1945–1954 to 1975–1983 (data are unavailable for 1984), the table estimates the four slope parameters of equations (6)–(8) using age-25 ever-born fertility. Panel A reports estimates of the overall intergenerational fertility association, β_{ct}^a , which is 0 in the 1945–1954 cohort but steadily grows to a statistically significant 0.08 by the 1975–1983 cohort. That is to say, among Bolivian women born just after World War II, childhood family size has no relation to adult fertility. But among their counterparts born three decades later, each additional sibling is associated with an additional one-twelfth of a child by age 25.

Panel B reports estimates of the “long” regression, showing that net of education, the intergenerational transmission of fertility starts positive at 0.01 and then grows to roughly 0.03 in later birth cohorts. Net of sibship size, education has a negative association with fertility across all cohorts, although the association is most negative for the most recent cohorts. Interpreted through the theoretical framework of Section 2, fertility patterns in all cohorts are consistent with a post-transition fertility regime. However, in panel C’s estimates of the “auxiliary” regression, the association of sibship size and education flips from positive to negative, consistent with a shift from pre- to post-transition patterns in the parents’ generation. Taken together, staggered shifts in the skill–fertility relationship across generations account for over half of the growth in the intergenerational fertility association.

4.2.2. Distribution of Parameter Estimates. The full-sample analysis applies these same methods to all 5-year country-cohorts, for both ever-born and surviving fertility. Table 2 summarizes the parameter estimates. Column (1) presents the mean and standard deviation of the parameter estimate across cells. The remaining columns summarize the distributions of the associated t -statistics, based on analytic standard errors clustered at the primary sampling unit level.

Two patterns emerge for intergenerational associations in both ever-born and surviving fertility. First, the central tendencies of β_{ct}^a and B_{ct}^a are close to zero, and the supports of their distributions contain both positive and negative values. Second, the dispersion of B_{ct}^a —from the “long” regression, which controls for education—is smaller than that of β_{ct}^a from the “short” regression. Heterogeneity in the role of education thus explains part of the observed heterogeneity in intergenerational fertility association. To shed additional light on this heterogeneity, Online Appendix Figure A.1 plots kernel densities of the estimated β_{ct}^a and B_{ct}^a across country-cohort cells, revealing that the distribution of B_{ct}^a has shorter right *and* left tails than the

TABLE 1. Sibship size, educational attainment, and age-25 fertility in Bolivia.

	1945–1954		1955–1964		1965–1974		1975–1983	
	Ever (1)	Surv. (2)	Ever (3)	Surv. (4)	Ever (5)	Surv. (6)	Ever (7)	Surv. (8)
<i>A. Short regression (dependent variable: # children at age 25)</i>								
No. siblings	0.0001 [0.016]	0.005 [0.012]	0.009 [0.007]	0.014 [0.006]	0.048 [0.007]	0.043 [0.006]	0.081 [0.008]	0.073 [0.007]
<i>B. Long regression (dependent variable: # children at age 25)</i>								
No. siblings	0.010 [0.015]	0.014 [0.015]	0.014 [0.007]	0.026 [0.074]	0.035 [0.006]	0.042 [0.002]	0.029 [0.007]	0.039 [0.008]
Years of education	-0.064 [0.007]	-0.030 [0.006]	-0.082 [0.003]	-0.053 [0.003]	-0.115 [0.003]	-0.090 [0.003]	-0.130 [0.003]	-0.110 [0.003]
<i>C. Auxiliary regression (dependent variable: years of education)</i>								
No. siblings	0.148 [0.048]	0.322 [0.059]	0.062 [0.024]	0.205 [0.029]	-0.112 [0.022]	-0.010 [0.027]	-0.399 [0.029]	-0.373 [0.034]
<i>D. Means and standard deviations</i>								
No. children	1.8 (1.6)	1.4 (1.3)	1.9 (1.6)	1.6 (1.3)	1.8 (1.5)	1.6 (1.3)	1.6 (1.4)	1.4 (1.2)
No. siblings	4.6 (2.9)	3.5 (2.4)	5.4 (3.0)	4.2 (2.4)	5.4 (2.9)	4.4 (2.4)	5.3 (2.8)	4.5 (2.4)
Years of education	4.7 (5.4)		6.1 (5.3)		7.5 (5.1)		9.0 (5.1)	
No. observations	1,808		7,758		10,090		6,834	

Notes: Brackets contain standard errors clustered at the level of the primary sampling unit; parentheses contain standard deviations.
Data source: 1994, 2003, and 2008 Bolivia Demographic and Health Surveys.

TABLE 2. Summary of age-25 parameter estimates.

	Mean (S.D.) (1)	Distribution of t -statistics (%)		
		$t \leq -1.96$ (2)	$-1.96 < t < 1.96$ (3)	$t \geq 1.96$ (4)
<i>A. Ever-born</i>				
β (overall association)	0.017 (0.030)	2	70	29
B (net transmission)	0.014 (0.020)	2	70	29
Γ (skill–fertility)	–0.098 (0.048)	90	29	<1
φ (sibsize–skill)	0.005 (0.149)	26	35	40
<i>B. Surviving</i>				
β (overall association)	0.005 (0.030)	9	75	16
B (net transmission)	0.007 (0.021)	6	77	17
Γ (skill–fertility)	–0.070 (0.050)	80	17	3
φ (sibsize–skill)	0.082 (0.165)	16	29	55

Notes: Sample includes 581,143 women from 258 country-cohort cells with at least 250 observations. S.D. = standard deviation of the parameter. Fertility associations are based on cumulative fertility at age 25. t -statistics are based on standard errors clustered at the primary sampling unit level.

distribution of β_{ct}^a . This finding suggests that education amplifies both positive and negative intergenerational fertility associations.

One interpretation is that intergenerational fertility associations are small everywhere, so that the distributions observed in Online Appendix Figure A.1 are the result of sampling variability. However, the distributions of t -statistics in Table 2 do not fit such an interpretation. At the 5% significance level, the ever-born fertility association is significantly positive in 29% of cells and significantly negative in 2%; the surviving fertility association is significantly positive in 16% of cells and significantly negative in 9%. The distribution of the surviving fertility associations contains too many positive values *and* too many negative values to be explained by randomness.

The amplifying role of education has two potential sources: heterogeneity in the association of education with fertility (Γ_{ct}) and heterogeneity in the association of sibship size with education (φ_{ct}). Theory predicts staggered reversals in these associations. The skill–fertility association flips first, inducing a flip in the next generation’s sibsize–skill association. For insight into which of these sources is at play, Table 2 also reports distributions of estimates and t -statistics for Γ_{ct} and φ_{ct} . The reversal of the skill–fertility association had already occurred before the sample cohorts began childbearing, with 90% of the estimates significantly negative for ever-born fertility and 80% for surviving fertility. In contrast, the distribution of the sibsize–skill association has significant mass in both tails, suggesting that some cohorts were born when Malthusian fertility patterns prevailed, so that children with higher skill parents had more siblings and obtained more education. For ever-born fertility, 40% of φ_{ct} estimates are significantly positive and 26% negative. For surviving fertility, 56% are positive and 16% negative.

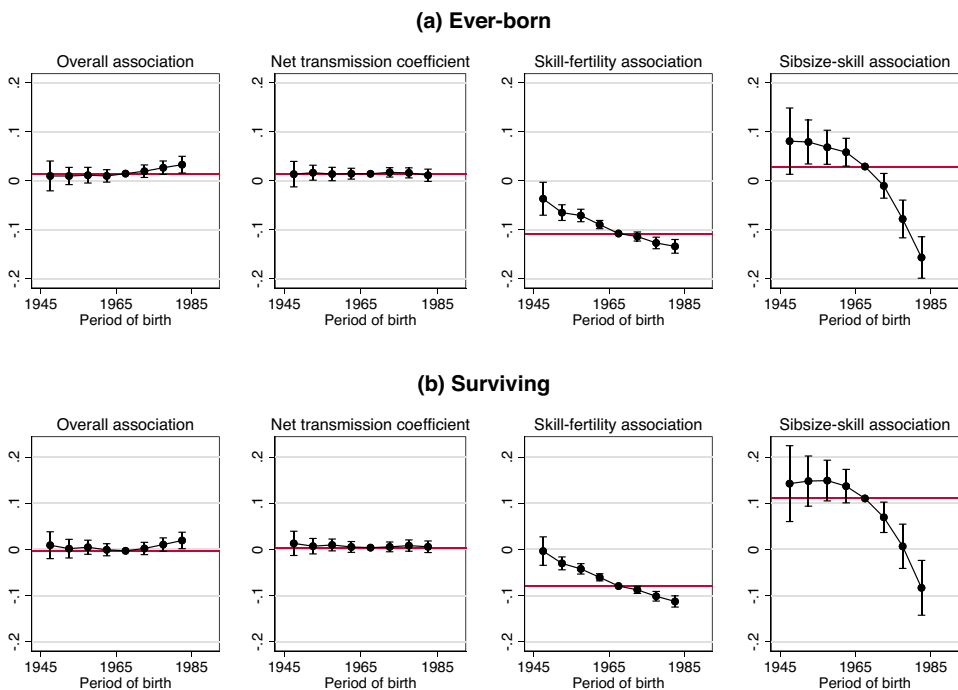


FIGURE 3. Cohort effects in parameter estimates. Sample includes 581,143 women from 258 country-cohort cells with at least 250 observations. Plots represent cohort effects from regressions of the estimated country-cohort parameters on country and cohort fixed effects. Capped spikes represent 95% confidence intervals based on bootstrapped standard errors. Omitted category is 1965–1969, the only cohort with data available from all countries. Horizontal lines are average parameter values across countries for the 1965–1969 cohort. Fertility associations are based on cumulative fertility at age 25.

4.2.3. Cohort Trends in Parameter Estimates. The preceding evidence suggests that most women in the sample bore children after transition onset, but some were born before. One can shed more light on this issue by considering how the parameters change on average across successive cohorts. To characterize these trends, I regress each estimated parameter on country fixed effects and cohort fixed effects, plotting the cohort effects in Figure 3. I set the omitted category to 1965–1969, the only cohort for which data are available for all countries, and then add the mean parameter value to the cohort effects, so the figure provides information about average levels and changes. The horizontal line reflects the 1965–1969 mean; the point estimates and 95% confidence intervals are for differences relative to this line.

Starting from the right-hand side of Figure 3, one can see clear evidence of a transition between cross-sectional fertility regimes. For both ever-born and surviving sibship size, the sibsize–skill association is positive on average for the 1965–1999 cohort, significantly more positive for earlier cohorts, and significantly more negative for later cohorts. Moving forward one generation, the skill–fertility association

is negative on average for the 1965–1969 cohort, but similar to the sibsize–skill association, it is significantly less negative for earlier cohorts, and significantly more negative for later cohorts. Meanwhile, the net transmission coefficient averages near zero with little change.

The intergenerational association equals the net transmission coefficient plus the product of the two skill-related associations. Since the transmission coefficient is constant while the skill-related associations become more negative across successive cohorts, intergenerational fertility associations should become more positive. Indeed, the left-most panels of Figure 3 indicate that intergenerational associations for both ever-born and surviving fertility have become significantly more positive since the 1965–1969 cohort. Magnitudes are not large: the intergenerational association averages 0.02–0.03 for the 1980–1984 cohort, implying that a woman with 10 siblings can expect to have 1/10 more children by age 25 than a woman with no siblings. Nevertheless, the data show a clear strengthening of the association, consistent with the theory.

4.2.4. Relationship Between Parameter Estimates. Although Figure 3 provides evidence of average changes across cohorts, one can glean further evidence of the link between intergenerational fertility associations and skill–fertility associations by directly relating them. Figure 4 carries out such an analysis. On the left-hand side, the figure draws scatterplots and local linear regressions (with confidence intervals based on bootstrapped pointwise standard errors) linking the intergenerational fertility association to the sibsize–skill association. Both the scatterplot and nonparametric fit reveal negative relationships for both ever-born and surviving fertility, with the scatterplot also suggesting regional variation. Latin American and Caribbean (LAC) cohorts have more negative sibsize–skill associations and more positive intergenerational fertility associations. In the starkest cases (recent cohorts in the Andes), a women with 10 siblings can expect to have 5 years less education and 1 more child than a woman with no siblings. At the other end of the spectrum (older cohorts in Africa), the woman with 10 siblings would expect to have 3 years less education and 1/3 fewer children than her counterpart without siblings. The intercepts of the local linear regressions are significantly positive at the 5% level, reflecting a net transmission coefficient that is on average greater than zero. As reported in the top-right corners each panel, OLS regressions on these scatterplots lead to significantly negative slopes of roughly -0.1 ($p < 0.01$) for both measures of fertility. Relative to the standard deviations in Table 2, these slopes imply that variation in the sibsize–education association explains half of the variation in the intergenerational fertility association.

Despite the apparent importance of regional variation, within-country variation produces similar results. The right-hand side of Figure 4 plots residuals after regressing the estimated parameters on country and cohort fixed effects. A negative slope obtains again, suggesting that as the sibsize–skill association turns more negative across successive cohorts within a country, the intergenerational fertility association turns more positive. The LAC region reaches furthest into the southeast and northwest quadrants, implying that the simultaneous drop in the sibsize–skill association and rise

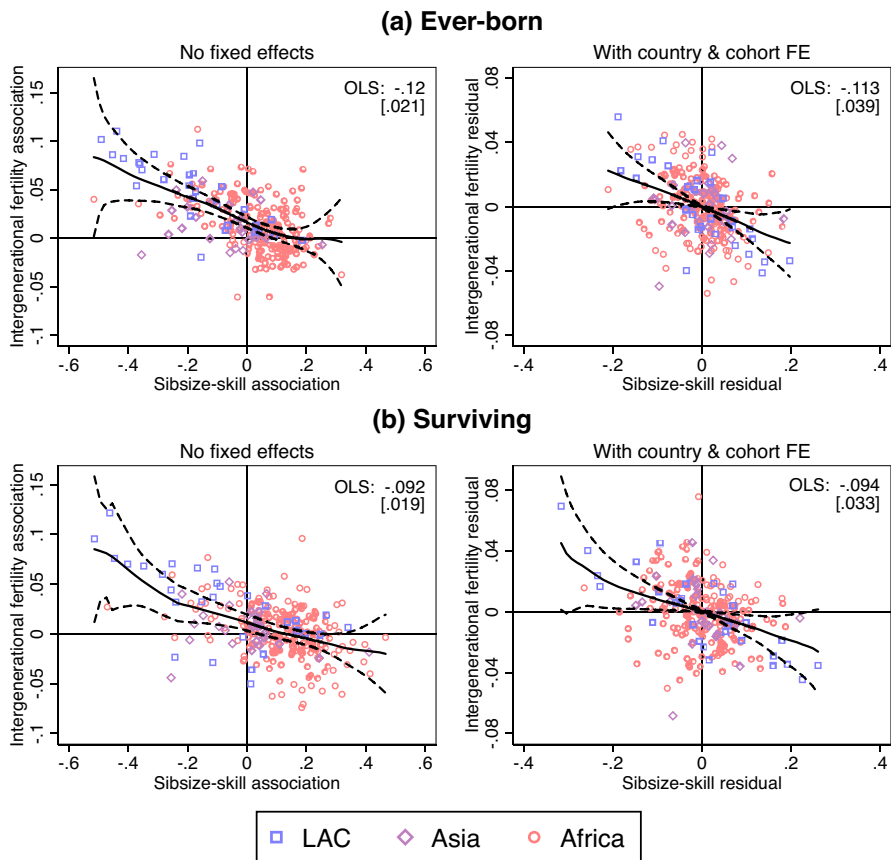


FIGURE 4. Intergenerational fertility associations versus sibsize–skill associations. Sample includes 581,143 women from 258 country-cohort cells with at least 250 observations. Solid curves are local linear regressions with bandwidths of 0.1; dashed curves are 95% confidence intervals based on bootstrapped pointwise standard errors. OLS results reported in the top right corner of each panel are slope coefficients from the analogous linear regressions, with bootstrapped standard errors in brackets. Fertility associations are based on cumulative fertility at age 25.

in the intergenerational fertility association were strongest in that region. As reported in the top-right corners, OLS estimates of the slopes are very similar with and without fixed effects, and they remain significant at the 1% level.

4.2.5. Extensions. The Online Appendix presents additional analyses on four themes: (i) the sensitivity of the results to the age at measurement, (ii) the role of place, (iii) the roles of marriage and fertility onset, and (iv) the aggregate predictors of the intergenerational fertility association.

How sensitive are the results to the age at measurement? Based on Figure 2, the preceding analysis focused on OLS estimates of β_{ct} using cumulative fertility at age 25 as the outcome. To shed light on robustness to alternative choices, Online

Appendix Figure A.2 compares local linear regressions of the intergenerational fertility association on the sibsize–skill association using OLS and Poisson models, with fertility measured at ages 20, 25, 30, 35, 40, and 45. All variants suggest that as the sibsize–skill association turns negative, the fertility association becomes more positive. The figure also plots the distribution of the sibsize–skill association for the cohorts old enough to be measured at 20, 25, 30, 35, 40, and 45. The younger the age at measurement, the more mass there is over negative values of the sibsize–skill association. Thus, the choice to measure fertility at age 25 is not key to the shape of the estimated relationship between β_{ct} and φ_{ct} , but it is key to guaranteeing that the sample include post-transition cohorts.

What is the role of place in driving the intergenerational fertility association? For instance, local average human capital may be more relevant than individual human capital in determining fertility behavior. To address this possibility, Online Appendix Figure A.3 compares the previous results with re-estimated associations in regressions with survey cluster fixed effects. These new associations are estimated using only within-cluster variation. Yet the results show a similarly-sloped, negative relationship between the intergenerational fertility association and the sibsize–skill association.

To what extent do the preceding results reflect changes in the ages at marriage and first birth? The fact that intergenerational fertility associations measured early in the reproductive lifecycle predict associations measured late in the reproductive lifecycle suggests that marriage and the initiation of childbearing may play an important role. Ordinary least squares estimation of equation (6) is inappropriate for answering this question because never-married and childless women have censored outcomes, so Online Appendix Figure A.4 estimates Cox hazard regressions in which the age at first marriage or first birth is the outcome. For both outcomes, both with and without country and cohort fixed effects, the results reveal that when women with more siblings obtain more education, they marry and begin having children later, but when such women obtain less education, they marry and begin having children earlier.

How does the intergenerational fertility association relate to economic and demographic aggregates? The aggregate predictors of the association can shed light on the mechanisms driving its changes, as well as their relation to theory. To this end, Online Appendix Table A.2 regresses the intergenerational fertility association on country and cohort fixed effects, plus log GDP per capita, the urbanization rate, the infant mortality rate, and the average and standard deviation of educational attainment among adults.²¹ Because the intergenerational association depends on fertility decisions in two generations, the regressions consider two measurements of each predictor, first in the five-year period of birth and then in the five-year period surrounding the 20th birthday. Of the five predictors, only average educational attainment has a significant relationship with the intergenerational association, and the

21. Women's wages and labor force participation would also be attractive covariates, given the potential role of women's work in the fertility transition. Unfortunately, panel data on these variables are sparse. Vogl (2016) analyzes the available data and finds that women's work plays no role in the reversal of fertility differentials.

period of birth appears more relevant than the period of young adulthood. For both ever-born and surviving fertility, a one-year increase in average educational attainment in the period of birth is associated with a strengthening of the intergenerational association by 0.02–0.03, or two-thirds of a standard deviation. These results are consistent with a role for human capital in driving the results. If the returns to individual human capital investment increase with the aggregate stock of human capital, then in the model of Section 2.2, a rising aggregate stock would first rupture intergenerational persistence in fertility and then restore it.²²

5. Composition Effects on Average Fertility

What do these strengthening intergenerational associations imply for the evolution of average fertility? This section estimates the composition effect of differential fertility among cohort t 's parents on the average fertility of cohort t . Of particular interest is how the composition effect varies with average fertility in cohort t , which speaks to how the dynamics of population composition affect the evolution of aggregate fertility rates.

5.1. Methods

For empirical application, the composition effect in Section 2 requires three modifications. First, the framework considered a population of one sex for analytical convenience, but the empirical measure must account for the reality of two sexes. As such, I refine the definition the composition effect to be the average number of children born to *women* minus the average number of grandchildren per *daughter* born to their mothers.²³ Second, Section 2 wrote the composition effect over the distribution of fertility in the grandparent generation, but the DHS offers data on the women themselves. Thus, the modified definition of the composition effect involves two ingredients: the average fertility of women from country-cohort ct , \bar{n}_{ct}^a , and their deweighted average fertility, \hat{n}_{ct}^a , which undoes the reweighting of the population due to differential fertility among their mothers. Let K be the maximum number of surviving females in a woman's sibship (including herself); η_{ctk} be the share of women from country-cohort ct with k surviving females in their sibships; and \bar{n}_{ctk}^a be the average fertility of women with k surviving females in their sibships. Then,

$$\bar{n}_{ct}^a = \sum_{k=1}^K \eta_{ctk} \bar{n}_{ctk}^a \quad \text{and} \quad \hat{n}_{ct}^a = \sum_{k=1}^K \left(\frac{\eta_{ctk}/k}{\sum_{l=1}^K \eta_{ctl}/l} \right) \bar{n}_{ctk}^a.$$

Third, because changing fertility levels complicate comparisons of composition effects at different stages of the fertility transition, I divide the absolute composition effect by

22. These results also confirm the ambiguous role of inequality in the presence of a hump-shaped relationship between the wage and fertility, noted in footnote 13.

23. A more detailed definition might explicitly consider men and the role of assortative mating, but the DHS only offers data on women's sibship sizes, making such an extension impossible to estimate.

the average fertility that would obtain in the absence of reweighting from differential fertility in the previous generation. This new measure, the *relative composition effect*, captures how the reweighting of the population affects average fertility in proportional terms. The prediction that the absolute composition effect becomes more positive after transition onset also applies to the relative composition effect.

For country-cohort ct , the relative composition effect on mean fertility at age a is

$$\delta_{ct}^a = \frac{\Delta_{ct}^a}{\hat{n}_{ct}^a} = \frac{\bar{n}_{ct}^a - \hat{n}_{ct}^a}{\hat{n}_{ct}^a}. \quad (9)$$

This expression is a simple nonlinear combination of the weighted and deweighted averages. The nonparametric estimator for the relative composition effect plugs in the empirical analogs of those averages. Keeping with Section 4, the measure of fertility is cumulative fertility at age 25. For conciseness, I report results only for children ever born; unreported results for surviving fertility are extremely similar. Notably, however, \hat{n}_{ct}^a reweights on the number of *surviving* sisters only, as deceased sisters are irrelevant to a cohort's composition in adulthood.

In the case of a linear conditional expectation function, the composition effect equals the intergenerational association times the variance-to-mean ratio of childhood family size.²⁴ To clearly link the composition effect estimates with the fertility transmission results of the previous section, I carry out this decomposition using sibship rather than sistership size.²⁵ For county-cohort ct , the decomposition is

$$\delta_{ct}^a = \left(\frac{\beta_{ct}}{\hat{n}_{ct}} \right) \left(\frac{\hat{\sigma}_{ct}^2}{\hat{s}_{ct}} \right), \quad (10)$$

where β_{ct} is the slope from a regression of ever-born fertility on surviving sibship size, and $\hat{\sigma}_{ct}^2$ and \hat{s}_{ct} are the deweighted variance and mean of sibship size, respectively. The relative composition effect has two components: a relative intergenerational association and a ratio. If the intergenerational association becomes positive during fertility decline, but the ratio stays constant, then the composition effect rises. Each of these components is separately estimable, and their product provides a parametric estimator of the composition effect.

5.2. Results

As in Section 4.2, I begin with case study evidence from Bolivia to build intuition. I then present estimates for all country cohort cells and track their evolution over the fertility transition.

24. If one adds a quadratic term to equation (6), the results suggest curvature in the conditional expectation function in some cases, with approximately 15% of country-cohorts showing significant squared terms. Consequently, one should interpret the decomposition as a descriptive tool, rather than taking literally the assumption of linearity.

25. Results are extremely similar if one changes the covariate to the surviving number of female siblings, which would more appropriately capture the dynamics of a two-sex population but would have a less obvious relation to Section 4.

TABLE 3. Composition effects on age 25 fertility in Bolivia.

	1945–1954 (1)	1955–1964 (2)	1965–1974 (3)	1975–1983 (4)
<i>A. Relative composition effects</i>				
Nonparametric	−0.032 [0.020]	−0.009 [0.008]	0.007 [0.009]	0.058 [0.011]
Parametric	−0.018 [0.023]	0.0009 [0.008]	0.038 [0.009]	0.093 [0.012]
<i>B. Components</i>				
Relative association	−0.009 [0.011]	0.0005 [0.005]	0.022 [0.005]	0.056 [0.007]
Variance/mean of sibsize	2.05 [0.07]	1.88 [0.05]	1.76 [0.03]	1.66 [0.05]
<i>C. Means and standard deviations</i>				
Children ever born	1.8 (1.6)	1.9 (1.6)	1.8 (1.5)	1.6 (1.4)
Deweighted children ever born	1.9 (1.7)	1.9 (1.6)	1.8 (1.5)	1.5 (1.3)
No. observations	1,808	7,758	10,090	6,834

Notes: Brackets contain standard errors block bootstrapped at the primary sampling unit level; parentheses contain standard deviations.

Data source: 1994, 2003, and 2008 Bolivia Demographic and Health Surveys.

5.2.1. Bolivian Case Study. The case study of Bolivia appears again in Table 3, using the same four decadal cohorts as Table 1. Panel A presents relative composition effects across cohorts, estimated first nonparametrically using equation (9) and then parametrically using equation (10). Panel B decomposes each parametric estimate into a relative fertility association and a variance-to-mean ratio. Panel C reports additional descriptive statistics. Because the estimands are nonlinear combinations of parameters, standard errors are block-bootstrapped at the primary sampling unit level.

In panel A, both the nonparametric and parametric estimates are consistent with a population that started at transition onset and then settled into a post-transition regime. The earliest cohort exhibits a marginally significant negative composition effect, implying that differential fertility in the previous generation *decreases* the cohort's average fertility, by 2%–3%. The nonparametric estimate for this cohort is more negative and more statistically significant ($p = 0.098$) than the parametric estimate, but both estimates display a marked upward trend across subsequent cohorts. The latest cohort exhibits a significantly positive composition effect using either estimator, such that differential fertility in the previous generation *increases* this cohort's average fertility by 6%–9%. The corresponding levels of fertility can be seen in the descriptive statistics at the bottom of the table. Deweighted average fertility starts higher than actual average fertility (1.9 vs. 1.8 children ever born) but ends lower (1.5 vs. 1.6 children ever born).

Panel B reveals that this increasing trend in the relative composition effect is driven by a rising relative intergenerational association, rather than a rising variance-to-mean ratio. The association is (insignificantly) negative for the earliest cohort but then swells to (a significant) 0.06 for the latest cohort, implying that each additional

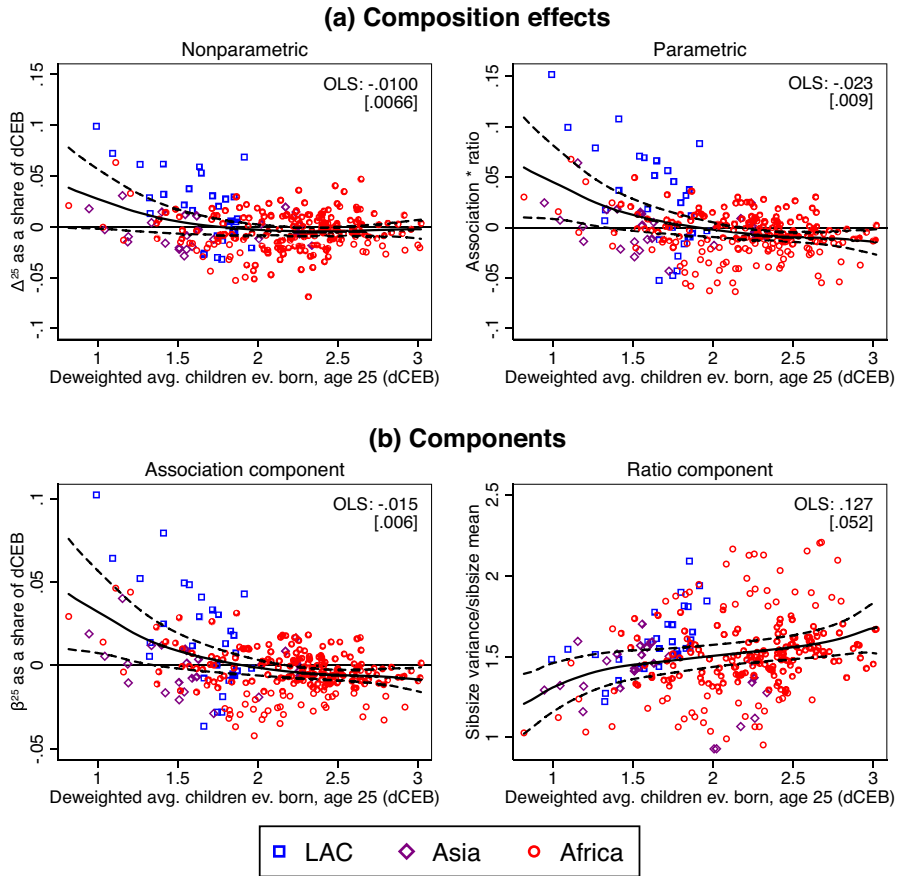


FIGURE 5. Composition effects on cohort average fertility. Sample includes 581,143 women from 258 country-cohort cells with at least 250 observations. Solid curves are local linear regressions with bandwidths of 0.5; dashed curves are 95% confidence intervals based on bootstrapped pointwise standard errors. OLS results reported in the top right corner of each panel are slope coefficients from the analogous linear regressions, with bootstrapped standard errors in brackets. Estimates are based on based on cumulative ever-born fertility at age 25.

sibling is associated with a 6% increase in fertility relative to the deweighted mean. Meanwhile, the variance-to-mean ratio of sibship size steadily declines across cohorts, from 2.1 to 1.7, thus acting to limit increases in the composition effect. However, this force lacks the strength to entirely offset the rising relative intergenerational association. Overall, the Bolivian data indeed suggest that composition effects turn positive as the fertility transition sets in, pushing back against decline of average fertility.

5.2.2. Composition Effects over the Fertility Transition. For the full sample, Figure 5 plots the composition effect and its components against deweighted average fertility,

along with local linear regression estimates. Using deweighted (rather than actual) average fertility on the x -axis eases interpretation because actual fertility is $(1 + \delta)\hat{n}$ when deweighted fertility is \hat{n} .

On the left side of panel (a), nonparametric estimates of equation (9) show the composition effect averaging near zero for levels of deweighted average fertility above 1.5. But below 1.5, the composition effect rises. At the lowest observed levels of fertility, differential fertility in the previous generation raises current mean fertility by 4% on average—with the regression function significantly different from zero at $p = 0.06$. OLS estimation on this scatterplot yields a negative slope of -0.010 ($p = 0.13$). If one uses an indicator for the bottom decile of deweighted average fertility instead of the continuous measure, the coefficient on that indicator is 0.024 ($p = 0.02$). Composition effects are higher when cohort fertility is lower.

On the right side of panel (a), parametric estimates based on equation (10) point to a similar but even more pronounced rise below 1.5. At the 5% level, the regression function is significantly positive at the lowest levels of deweighted average fertility and significantly negative at the highest levels. OLS estimation on this scatterplot also yields a significant negative slope ($p = 0.01$). Together, then, both composition effect estimators suggest that endogenous changes in population composition push back against aggregate fertility decline late in the fertility transition. Consistent with the patterns in Section 4, the growth of the composition effect late in the fertility transition is especially apparent in the LAC region.

Panel (b) of Figure 5 decomposes the parametric estimator into the association and ratio components, revealing that the rise in composition effects as fertility falls can be attributed entirely to rising intergenerational associations. The relative intergenerational association decreases with the level of deweighted fertility, whereas the variance-to-mean ratio increases with it. Both of these relationships are characterized by OLS slope coefficients that are significant at the 5% level. The results for the full sample thus mimic the case study evidence from Bolivia.

Can these composition effects explain the fertility “stalls” that Bongaarts (2006, 2008) identified in several populations? DHS sibling history data are available for three of the six countries that Bongaarts (2006) originally singled out for their “stalls”: Dominican Republic, Kenya, and Peru. Online Appendix Figure A.5 plots mean and de-weighted mean fertility across cohorts for these countries, with three takeaways. First, none of the three countries show stalls in cohort fertility decline, at least as measured at age 25, which contrasts Bongaarts’ results for the total fertility rate.²⁶ Second, absent the reweighting of the population due to differential fertility, Kenya and Peru would have started with slightly higher fertility and ended with slightly lower fertility, implying that composition effects initially promoted fertility decline but now slow it. Third, the Dominican Republic exhibits positive composition effects for all

26. Section 6 analyzes composition effects on the total fertility rate, but unfortunately too few DHS surveys have sibling histories to reliably assess their contributions to country-specific trends in total fertility.

cohorts because the intergenerational fertility association was already positive for the earliest cohorts in the sample. Overall, these results suggest the composition effects do moderate the pace of fertility decline in the expected way but are not the main driver of the dynamics of average fertility.

6. Implications for Period Fertility Rates

Cumulative fertility at age 25 is an uncommon measure, making the cohort results difficult to interpret. This section estimates the implications for the total fertility rate (TFR), or the number of children a woman would expect to bear if she experienced current age-specific fertility rates throughout her reproductive lifecycle. TFR is a period measure of fertility, summing over the cross-sectional distribution of age-specific fertility rates, so each DHS survey provides exactly one estimate.

6.1. Methods

To analyze TFR, let b_{ict}^a be indicator for whether woman i of age a from country c and birth cohort t gave birth in the year preceding the survey. Let the τ be the survey year, so that the cohort average \bar{b}_{ct}^a is an age-specific fertility rate for age a in year $\tau = t + a$. Similarly, the deweighted cohort average \hat{b}_{ct}^a is the age-specific fertility rate that would have obtained absent the influence of differential fertility on population composition. The total fertility rate and deweighted total fertility rate sum over these age-specific rates. For country c in year τ :

$$TFR_{c\tau} = 5 \sum_a \bar{b}_{c,\tau-a}^a \quad \text{and} \quad dTFR_{c\tau} = 5 \sum_a \hat{b}_{c,\tau-a}^a.$$

The summations are multiplied by five because I use five-year age groups, from 15–19 to 45–49. The composition effect of differential fertility on TFR is the relative difference between actual TFR and the TFR that would obtain if women from different sibship sizes were equally represented within their age group:

$$\delta_{c\tau} = \frac{TFR_{c\tau} - dTFR_{c\tau}}{dTFR_{c\tau}}. \quad (11)$$

As in the cohort analysis, this expression is a nonlinear combination of weighted and deweighted averages. The empirical analog is a nonparametric estimator for the composition effect on TFR.

For the linear case, the cohort analysis decomposed the composition effect into a relative intergenerational association and variance-mean ratio. For TFR, the decomposition becomes complicated because the numerator of the right-hand side of equation (11) sums 7 age-group-specific absolute composition effects, each of which has a separate multiplicative decomposition. However, one can approximate the decomposition by assuming that either the association component or the ratio component is constant across age groups. Because the paper focuses on variation in

intergenerational associations, I hold the variance-to-mean ratio at its average:

$$\delta_{c\tau} = \frac{\sum_a \beta_{c,\tau-a}^a \frac{\hat{\sigma}_{c,\tau-a}^2}{\hat{\mu}_{c,\tau-a}}}{dTFR_{c\tau}} \approx \left(\frac{5 \sum_a \beta_{c,\tau-a}^a}{dTFR} \right) \left(\frac{1}{7} \sum_a \frac{\hat{\sigma}_{c,\tau-a}^2}{\hat{\mu}_{c,\tau-a}} \right), \quad (12)$$

where $\beta_{c,\tau-a}^a$ is the coefficient from a regression of an indicator for a birth in the year preceding the survey on surviving sibship size for respondents aged a , whereas $\hat{\sigma}_{c,\tau-a}^2$ and $\hat{\mu}_{c,\tau-a}$ are the deweighted variance and mean of sibship size, respectively. In the approximate decomposition of equation (12), $\delta_{c\tau}$ again has two parts: a relative association and a ratio. In the first, the total fertility association $5 \sum_a \beta_{c,\tau-a}^a$, which mimics the total fertility rate by summing over the cross-sectional distribution of age-specific fertility associations, is divided by the deweighted TFR. In the second, the ratio of the variance to the mean of sibship size is averaged across the seven age groups. As in Section 5, the product of these components provides a parametric estimator for the composition effect, which in this case is approximate.

6.2. Results

For each of the 81 surveys in the sample (not including Nepal 1996, which lacks representative information on younger, unmarried women), Figure 6 plots the composition effect and its components against deweighted TFR, along with local linear regression estimates. The results mirror the cohort results in the previous section. In panel (a), nonparametric estimates of the composition effect average near zero when deweighted TFR exceeds 4, but below this threshold, they turn positive. At the lowest observed levels of deweighted average fertility, differential fertility in the previous generation raises average fertility by 4% on average ($p < 0.01$). OLS estimates also show a significantly negative slope ($p = 0.02$), such that each additional child per woman is associated with a 0.7-point lower composition effect. Parametric estimates based on the approximation in equation (12) display similar patterns, although as in the cohort results, they are larger in magnitude and more statistically significant. In a notable difference from the cohort results, neither regression function ever turns significantly negative.

Here again, the association component rather than the ratio component drives the evolution of the composition effect over the fertility transition. As deweighted TFR falls below 4 in panel (b) of Figure 6, the total fertility association rises dramatically as a share of deweighted TFR, such that at the lowest observed fertility levels, each additional sibling is associated with a 5% increase in the number of children per woman. In contrast to the cohort results, the average variance-to-mean ratio for sibship size does not appreciably change with the level of fertility.

Overall, the analysis of period fertility rates has similar conclusions to the analysis of cohort fertility rates. In the later phases of the fertility transition, the composition effect raises average fertility. With nonparametric estimates of 4% on average (6%–10% in the most pronounced cases), these results explain a small but systematic feature of aggregate fertility dynamics.

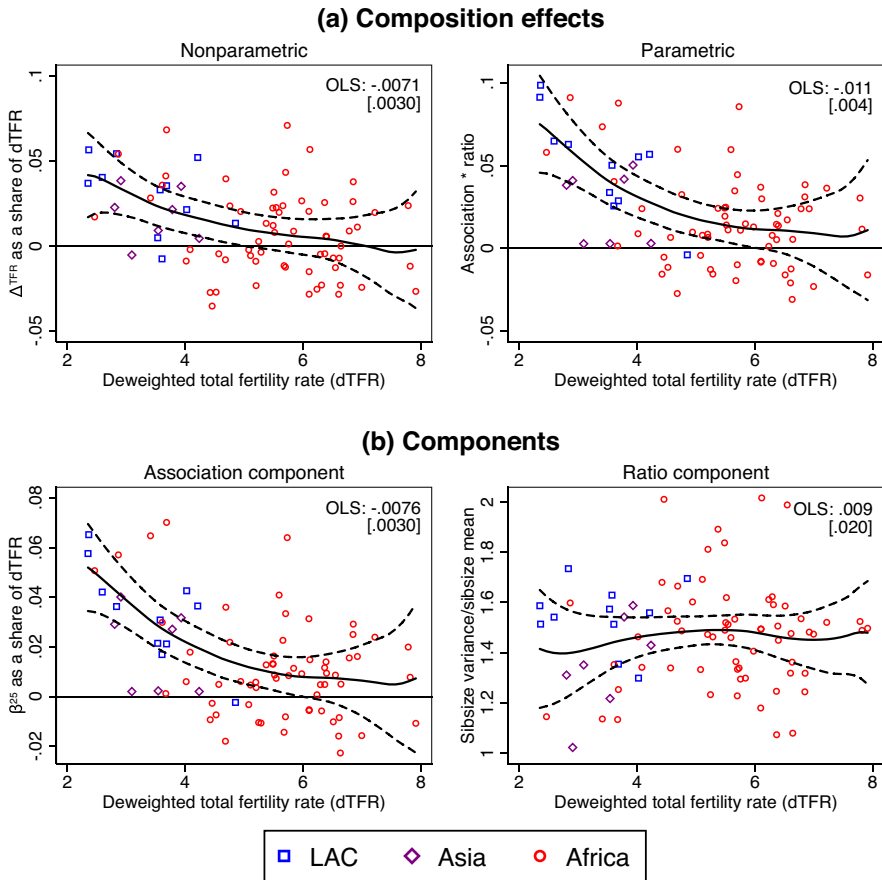


FIGURE 6. Composition effects on the total fertility rate. Sample includes 81 surveys. Solid curves are local linear regressions with bandwidths of 1; dashed curves are 95% confidence intervals based on boot-strapped pointwise standard errors. OLS results reported in the top right corner of each panel are slope coefficients from the analogous linear regressions, with boot-strapped standard errors in brackets.

7. Conclusion

The question of whether girls from large families tend to bear many children in adulthood has drawn the attention of social scientists and statisticians for over a century. Nevertheless, existing research has shed limited light on how this association evolves over the course of the fertility transition, and on what implications it has for aggregate fertility outcomes. This paper fills that gap on two levels.

It first theoretically explores how intergenerational associations aggregate up to the population level and how they evolve in economic models of the demographic transition. The theoretical results highlight the importance of the changing relationship between skill and fertility. Intergenerational fertility associations—and therefore also

composition effects—turn positive when fertility differentials by skill are aligned across generations, which occurs before and after, but not during, transition onset. As a result, differential fertility initially encourages the decline of aggregate fertility but then hinders it.

Second, the empirical analysis confirms these predictions in data on mother–daughter pairs from 40 developing countries over half a century. In these data, intergenerational associations grow after transition onset, as the link between sibship size and education flips from positive to negative. Due to this change in intergenerational associations, the composition effect of differential fertility on average fertility turns positive as the fertility transition progresses.

The paper’s approach provides a new demographic lens for understanding the pace of the global decline of fertility, the subject of a large literature in economics (Schultz 1997; Galor 2011; de la Croix 2013). From a broader economic perspective, the results are of interest not just because they clarify aggregate fertility dynamics but also because they demonstrate a unique way in which intergenerational associations aggregate up to population-level dynamics. In this sense, this paper is related to the literature exploring how the intergenerational transmission of economic status affects the dynamics of the income distribution (Becker and Tomes 1979; Goldberger 1989).

Although the paper breaks new ground on the changing causes and consequences of fertility transmission, several questions remain open. First, although fertility differentials by female education clearly influence intergenerational fertility associations, other sources of intergenerational persistence, such as fecundity and culture, may also play a role. A fuller model of the evolution of intergenerational transmission would also take these factors into account, although data limitations hinder tests of such a model. Second, although the paper provides evidence that changes in differential fertility and population composition interact to increase the composition effect of differential fertility, future research could further draw out the connections to the pace of fertility decline. Finally, the analysis here has not considered other demographic influences on the time path of aggregate fertility, such as assortative mating, or intergenerational influences that span more than two generations (Mare 2011). Investigations into the consequences of these other mechanisms may shed further light on the microlevel demographic phenomena influencing the pace of aggregate change.

References

- Anderton, Douglas L., Noriko O. Tsuya, Lee L. Bean, and Geraldine P. Mineau (1987). “Intergenerational Transmission of Relative Fertility and Life Course Patterns.” *Demography*, 24, 467–480.
- Axinn, William G., Marin E. Clarkberg, and Thornton Arland (1994). “Family Influences on Family Size Preferences.” *Demography*, 31, 65–79.
- Barban, Nicola, Rick Jansen, Ronald De Vlaming, Ahmad Vaez, Jornt J. Mandemakers, Felix C. Tropf, Xia Shen, et al. (2016). “Genome-Wide Analysis Identifies 12 Loci Influencing Human Reproductive Behavior.” *Nature Genetics*, 48, 1462–1472.

- Becker, Gary S. (1981). *A Treatise on the Family*. Harvard University Press, Cambridge, MA.
- Becker, Gary S. and Nigel Tomes (1979). "An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility." *Journal of Political Economy*, 87, 1153–1189.
- Ben-Porath, Yoram (1975). "First-Generation Effects on Second-Generation Fertility." *Demography*, 12, 397–405.
- Bengtsson, Tommy and Martin Dribe (2014). "The Fertility Transition at the Micro Level: Socioeconomic Status, Income and Fertility in Southern Sweden 1815–1939." *Demographic Research*, 30, 493–534.
- Bhalotra, Sonia and Samantha Rawlings (2013). "Gradients of the Intergenerational Transmission of Health in Developing Countries." *Review of Economics and Statistics*, 95, 660–672.
- Björklund, Anders, Mikael Lindahl, and Erik Plug (2006). "The Origins of Intergenerational Associations: Lessons from Swedish Adoption Data." *Quarterly Journal of Economics*, 121, 999–1028.
- Björklund, Anders and Markus Jäntti (1997). "Intergenerational Income Mobility in Sweden Compared to the United States." *American Economic Review*, 87(5), 1009–1018.
- Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes (2005). "Why the Apple Doesn't Fall Far: Understanding Intergenerational Transmission of Human Capital." *American Economic Review*, 95(1), 437–449.
- Bongaarts, John (2006). "The Causes of Stalling Fertility Transitions." *Studies in Family Planning*, 37, 1–16.
- Bongaarts, John (2008). "Fertility Transitions in Developing Countries: Progress Or Stagnation?" *Studies in Family Planning*, 39, 105–110.
- Boyd, Robert and Peter J. Richerson (1988). *Culture and the Evolutionary Process*. University of Chicago Press, Chicago.
- Cavalli-Sforza, Luigi Luca, and Marcus W. Feldman (1981). *Cultural Transmission and Evolution: A Quantitative Approach*. Princeton University Press, Princeton.
- Chabé-Ferret, Bastien (2019). "Adherence to Cultural Norms and Economic Incentives: Evidence from Fertility Timing Decisions." *Journal of Economic Behavior & Organization*, 162, 24–48.
- Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez (2014). "Where is The Land of Opportunity? The Geography of Intergenerational Mobility in the United States." *Quarterly Journal of Economics*, 129, 1553–1623.
- Chevalier, Arnaud, Kevin Denny, and Dorren McMahon (2009). "A Multi-Country Study of Intergenerational Educational Mobility." In *Education and Inequality Across Europe*, edited by Peter Dolton, Rita Asplundh, and Erling Barth. Edward Elgar, London.
- Clark, Gregory (2007). *A Farewell to Alms: A Brief Economic History of the World*. Princeton University Press, Princeton.
- Clark, Gregory and Neil Cummins (2015). "Malthus to Modernity: Wealth, Status, and Fertility in England, 1500–1879." *Journal of Population Economics*, 28, 3–29.
- Corak, Miles (2013). "Income Inequality, Equality of Opportunity and Intergenerational Mobility." *Journal of Economic Perspectives*, 27(3), 79–102.
- Currie, Janet and Enrico Moretti (2003). "Mother's Education and the Intergenerational Transmission of Human Capital: Evidence from College Openings." *Quarterly Journal of Economics*, 118, 1495–1532.
- Daudin, Guillaume, Raphaël Franck, and Hillel Rapoport (2019). "Can Internal Migration Foster the Convergence in Regional Fertility Rates? Evidence from Nineteenth Century France." *Economic Journal*, 129, 1618–1692.
- De la Croix, David (2013). *Fertility, Education, Growth, and Sustainability*. Cambridge University Press, Cambridge.
- De la Croix, David and Matthias Doepke (2003). "Inequality and Growth: Why Differential Fertility Matters." *American Economic Review*, 93(4), 1091–1113.
- De la Croix, David and Faustine Perrin (2018). "How Far Can Economic Incentives Explain the French Fertility and Education Transition?" *European Economic Review*, 108(September), 221–245.

- Dhar, Diva, Tarun Jain, and Seema Jayachandran (2019). "Intergenerational Transmission of Gender Attitudes: Evidence from India." *Journal of Development Studies*, 55, 2572–2592.
- Duncan, Otis Dudley, Ronald Freedman, J. Michael Coble, and Doris P. Slesinger (1965). "Marital Fertility and Size of Family of Orientation." *Demography*, 2, 508–515.
- Fernández, Raquel and Alessandra Fogli (2009). "Culture: An Empirical Investigation of Beliefs, Work, and Fertility." *American Economic Journal: Macroeconomics*, 1, 146–177.
- Fernández, Raquel and Richard Rogerson (2001). "Sorting and Long-Run Inequality." *Quarterly Journal of Economics*, 101, 1305–1341.
- Fisher, Ronald A. (1930). *The Genetical Theory of Natural Selection*. Clarendon Press, Oxford.
- Fuller, Wayne A. (1987). *Measurement Error Models*. Wiley, New York.
- Galor, Oded (2011). *Unified Growth Theory*. Princeton University Press, Princeton.
- Galor, Oded and Marc Klemp (2019). "Human Genealogy Reveals a Selective Advantage to Moderate Fecundity." *Nature Ecology & Evolution*, 3, 853–857.
- Galor, Oded and Stelios Michalopoulos (2012). "Evolution and the Growth Process: Natural Selection of Entrepreneurial Traits." *Journal of Economic Theory*, 147, 759–780.
- Galor, Oded and Omer Moav (2002). "Natural Selection and the Origin of Economic Growth." *Quarterly Journal of Economics*, 117, 1133–1192.
- Galor, Oded and Omer Ozak (2016). "The Agricultural Origins of Time Preference." *American Economic Review*, 106(10), 3064–3103.
- Galor, Oded and David N. Weil (1996). "The Gender Gap, Fertility, and Growth." *American Economic Review*, 86(3), 374–387.
- Goldberger, Arthur S. (1989). "Economic and Mechanical Models of Intergenerational Transmission." *American Economic Review*, 79(3), 504–513.
- Goldberger, Arthur S. (1991). *A Course in Econometrics*. Harvard University Press, Cambridge, MA.
- Haider, Steven and Gary Solon (2006). "Life-Cycle Variation in the Association between Current and Lifetime Earnings." *American Economic Review*, 96(4), 1308–1320.
- Hazan, Moshe and Binyamin Berdugo (2002). "Child Labour, Fertility, and Economic Growth." *Economic Journal*, 112, 810–828.
- Hertz, Tom, Tamara Jayasundera, Patrizio Piraino, Sibel Selcuk, Nicole Smith, and Alina Verashchagina (2007). "The Inheritance of Educational Inequality: International Comparisons and Fifty-Year Trends." *BE Journal of Economic Analysis & Policy*, 7.
- Huestis, R. R. and Aline Maxwell (1932). "Does Family Size Run in Families?" *Journal of Heredity*, 23, 77–79.
- Jones, Larry E., Alice Schoonbroodt, and Michéle Tertilt (2010). "Fertility Theories: Can They Explain the Negative Fertility-Income Relationship?" In *Demography and the Economy*, edited by J.B. Shoven. University of Chicago Press, Chicago, pp. 43–100.
- Kahn, Joan R. and Kay E. Anderson (1992). "Intergenerational Patterns of Teenage Fertility." *Demography*, 29, 39–57.
- Keyfitz, Nathan (1971). "On the Momentum of Population Growth." *Demography*, 8, 71–80.
- Kolk, Martin, Daniel Cownden, and Magnus Enquist (2014). "Correlations in Fertility Across Generations: Can Low Fertility Persist?" *Proceedings of the Royal Society B: Biological Sciences*, 281, 20132561.
- Kremer, Michael (1997). "How Much Does Sorting Increase Inequality?" *Quarterly Journal of Economics*, 97, 115–139.
- Lam, David (1986). "The Dynamics of Population Growth, Differential Fertility, and Inequality." *American Economic Review*, 76(5), 1103–1116.
- Lam, David and Letícia Marteleto (2013). "Family Size of Children and Women During the Demographic Transition." Working paper, University of Michigan.
- Mare, Robert D. (2011). "A Multigenerational View of Inequality." *Demography*, 48, 1–23.
- Moav, Omer (2005). "Cheap Children and the Persistence of Poverty." *Economic Journal*, 115, 88–110.
- Murphy, Michael (2009). "Is The Relationship Between Fertility of Parents and Children Really Weak?" *Biodemography and Social Biology*, 46, 122–145.
- Murphy, Michael (2012). "Intergenerational Fertility Correlations in Contemporary Developing Counties." *American Journal of Human Biology*, 24, 696–704.

- Murphy, Michael and Duolao Wang (2003). "The Impact of Intergenerationally-Transmitted Fertility and Nuptuality on Population Dynamics in Contemporary Populations." In *Biodemography of Human Reproduction and Fertility*, edited by Joseph L. Rodgers and Hans-Peter Kohler. Kluwer Academic Publishers, Boston, pp. 209–228.
- Pearson, Karl, Lee Alice, and Bramley-Moore Leslie (1899). "Inheritance of Fertility in Man, and of Fecundity in Thoroughbred Racehorses." *Philosophical Transactions of the Royal Society of London, Series A*, 192, 257–330.
- Preston, Samuel H. (1976). "Family Sizes of Children and Family Sizes of Women." *Demography*, 13, 105–114.
- Sacerdote, Bruce (2007). "How Large are the Effects from Changes in Family Environment? A Study of Korean American Adoptees." *Quarterly Journal of Economics*, 122, 119–157.
- Schoumaker, Bruno (2014). *Quality and Consistency of DHS Fertility Estimates, 1990 to 2012*. DHS Methodological Reports No. 12. ICF International, Rockville, Maryland.
- Schultz, T. Paul (1997). "Demand for Children in Low Income Countries." In *Handbook of Population and Family Economics*, edited by Mark Rosenzweig and Oded Stark. Elsevier, Amsterdam, pp. 349–430.
- Skirrbek, Vegard (2008). "Fertility Trends by Social Status." *Demographic Research*, 18, 145–180.
- Spalaore, Enrico and Romain Wacziarg (2019). "Fertility and Modernity." NBER Working Paper No. 25957.
- Treloar, S.A. and N.G. Martin (1990). "Age at Menarche as a Fitness Trait: Nonadditive Genetic Variance Detected in a Large Twin Sample." *American Journal of Human Genetics*, 47, 137–148.
- Van den Akker, O.B.A., G.S. Stein, M.C. Neale, and R.M. Murray (1987). "Genetic and Environmental Variation in Menstrual Cycle: Histories of Two British Twin Samples." *Acta Geneticae Medicae Et Gemellologiae: Twin Research*, 36, 541–548.
- Vogl, Tom (2016). "Differential Fertility, Human Capital, and Development." *Review of Economic Studies*, 83, 365–401.
- Wise, Jeffrey M. and Spencer J. Condie (1975). "Intergenerational Fertility throughout Four Generations." *Biodemography and Social Biology*, 22, 144–150.

Supplementary Data

Supplementary data are available at [JEEA](https://academic.oup.com/jeea) online.