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AGGREGATING THE FERTILITY TRANSITION: INTERGENERATIONAL DYNAMICS IN QUALITY AND QUANTITY

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ABSTRACT

Fertility change is distinct from other forms of social and economic change because it directly alters the size and composition of the next generation. This paper studies how changes in population composition over the fertility transition feed back into the evolution of average fertility across generations. Theory predicts that changes in the relationship between human capital and fertility first weaken and then strengthen fertility similarities between mothers and daughters, a process that first promotes and then restricts aggregate fertility decline. Consistent with these predictions, microdata from 40 developing countries over the second half of the 20th century show that intergenerational fertility associations strengthen late in the fertility transition, due to the alignment of the education-fertility relationship across generations. As fertility approaches the replacement level, the strengthening of these associations reweights the population to raise aggregate fertility rates, pushing back against aggregate fertility decline.

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1 Introduction

Research in macroeconomics has shown increasing interest in whether and how heterogeneity across agents affects aggregate outcomes. In the study of economic development and growth, classic work on this topic (Banerjee and Newman 1993; Galor and Zeira 1993) focuses on how capital market imperfections interact with the distribution of wealth to affect development in the long run. More recent work seeks to model the interplay of these forces with demographic change (Galor and Moav 2002; Hazan and Berdugo 2002; de la Croix and Doepke 2003; Moav 2005). Because the escape from the Malthusian trap commonly coincides with the demographic transition (Galor 2011), an understanding of this economic-demographic interplay may be crucial for theories of current and historical economic growth. In this context, heterogeneity becomes especially interesting because it may feed back into the dynamics of population composition, with implications for the pace of aggregate change. Families with high relative fertility in one generation comprise a larger share of the next.

This paper studies how skill heterogeneity combines with decisions regarding the quality and quantity of children to influence the path of aggregate fertility decline across generations. Fertility decline—itself a transformation of social and economic life—plays a potentially important role in generating economic growth (Ashraf, Weil, and Wilde 2013), and its timing and pace present an important set of puzzles to economists and other social scientists. As its primary contribution, this paper focuses on an under-explored demographic mechanism influencing its pace. The core insight is that the fertility transition occurs unevenly, changing the relative fertility levels and population shares of different skill groups. Different lineages undergo fertility transitions at different times. As documented by Bengtsson and Dribe (2014), Clark and Cummins (2015), and Vogl (2016), the history of differential fertility spans two regimes, Malthusian and modern. In the past, when Malthusian population dynamics prevailed, higher-skill parents maintained higher levels of both fertility and child investment. But around the time of the demographic transition, their fertility fell below that of the lower-skilled, even as they continued to invest more in their children. Existing theoretical research (Galor and Moav 2002; Galor and Michalopoulous 2012) argues that these changes in differential fertility alter the skill composition of the population in the next generation, with important consequences for economic growth and other forms of aggregate progress.[1]

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[1] See also Clark (2007). These theories have much in common with the eugenic arguments of Francis Galton, Karl Pearson, and Ronald Fisher (Kevles 1985).

Building on that literature, this paper theoretically explores implications for the path of aggregate fertility and then quantifies these implications using micro-data from 40 developing countries. The main theoretical result is that forces commonly associated with the fertility transition—such as rising living standards and rising returns to human capital investment—induce compositional shifts that initially promote fertility decline and then restrain it. This result squares well with evidence from the demography literature (Bongaarts 2006, 2008) that following periods of sustained fertility decline, many populations "stall" at fertility levels well above the replacement level. A key determinant of these compositional shifts is the reduced-form association between a mother's fertility and her daughter's fertility, which provides a useful estimand for the empirical work. The theoretical framework predicts that within the Malthusian regime or the modern regime, this association is positive, but for the transitional generation between regimes, the association turns negative. Higher-skill parents bear more children and invest more in their human capital, but when their children grow up, their greater human capital decreases their own fertility.

Using 82 Demographic and Health Surveys, the paper thus estimates mother-daughter associations in fertility and their determinants in birth cohorts spanning the second half of the twentieth century from 40 developing countries. The results indicate that women of these cohorts bear children predominantly in the modern regime, when fertility declines with skill. But while more recent cohorts were also born in the modern regime, earlier cohorts in some countries are part of a transitional generation born in the Malthusian regime, when fertility rises with skill. Education thus negatively predicts fertility in all cohorts, but the association of childhood family size with education flips from positive the negative. As a result, in more recent cohorts, women with more siblings bear more children in adulthood; this relationship is significantly weaker in earlier cohorts, and in some cases, women with more siblings bear fewer children in adulthood. This striking finding highlights how the fertility transition reverses relative fertility levels across lineages within a single generation. The lineages with the most children per parent become the lineages with the fewest.

The theoretical framework rationalizes these changes as stemming from either rising productivity or increases in the return to investment in human capital (equivalently, decreases in the cost of schooling). Past research (Vogl 2016) finds that changes in differential fertility in sample countries were more consistent with the latter mechanism, involving the net return to parental investment in their children's human capital. In this paper, the role of human capital receives further support from analyses of the aggregate predictors of the intergenerational fertility association. Net of country and cohort fixed effects, GDP per capita, urbanization, and child mortality do not predict the association, but rising educational attainment—in the sample generation or in their parents' generation—is correlated with a rising intergenerational fertility association.

Yet the paper's core demographic insight about the aggregate consequences of changing intergenerational fertility associations is independent of the mechanism driving them. Because the intergenerational fertility association becomes stronger, the population share of high-fertility parents rises as a population approaches low fertility, pushing back against aggregate fertility decline. To quantify this phenomenon, the paper non-parametrically estimates the difference between the average number of children among mothers and the average number of grandchildren per daughter among grandmothers. This gap, which I term the *composition effect*, captures the extent to which heterogeneity in fertility across women who grew up in families of different size affects average fertility.[2] Estimating this effect at the cohort level, I find that the composition effect becomes significantly stronger as cohort fertility declines; well into the fertility transition, heterogeneity in fertility across mothers in one generation raises the mean fertility of their daughters by as much as 10 percent, and by 4 percent on average. To link these cohort-level associations to 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 as TFR declines. In populations with TFRs less than 3, differential fertility raises TFR by as much as 6 percent, and by 4 percent on average.

These findings demonstrate the role of heterogeneity in driving aggregate fertility dynamics. In this sense, they relate to the economics literature on how micro-level demographic phenomena like differential fertility and assortative mating aggregate up to the population or economy (Kremer 1993; Lam 1986; 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, yielding results that may help resolve the puzzle of fertility "stalls."[3] The

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[2] The composition effect of differential fertility bears similarities to the stable population theory concept of 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.

[3] Indeed, my data contain three of the six countries that Bongaarts (2003) singles out for having "stalls:" Dominican Republic, Kenya, and Peru. All three exhibit recent upward swings in composition effects on cohort fertility. Composition effects on TFR are significantly positive in Dominican Republic and Peru but not Kenya.

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 (2014), Preston argues 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 as 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 both across countries (Björklund and Jantti 1997; Solon 1999; Corak 2013) and across subnational areas within a country (Chetty et al. 2014). International comparisons are also available for intergenerational associations in of other outcomes, including educational attainment (Hertz et al. 2007; Chevalier, Denny, and McMahon 2009) and health (Bhalotra and Rawlings 2013). In the field of demography, interest in the association of mothers' and daughters' fertility dates back over a century, to one of the earliest applications of the correlation coefficient (Pearson et al. 1899).[4] Summarizing and extending this literature, Murphy (1999, 2012) finds that the association strengthened recently in rich countries and that it is weaker in poor than in rich countries. This paper further extends Murphy's analysis to shed light on changes over time within many countries, linking it to a broader theory of aggregate demographic change.[5]

More broadly, the paper contributes to the economics literature on the demographic transition and its relation to economic development (Galor 2011; de la Croix 2013). In both its theoretical and empirical facets, this work has focused mostly on aggregate demographic and economic variables, with a small subset of the theoretical literature exploring the role of within-population hetero-

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[4] 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 et al. (1994).

[5] Two recent contributions to biodemography (Murphy and Wang 2003; Kolk, Cownden, and Enquist 2014) study how intergenerational fertility associations affect the time series of aggregate fertility rates, but only in the context of highly stylized micro-simulation models.

geneity. While research in development economics has given more attention to within-population heterogeneity (Schultz 1997), its primary goal has been to understand the determinants of fertility choice in poor countries, not to shed light on how heterogeneity affects the pace of aggregate change. By analyzing heterogeneity and its consequences for many countries over half a century, this paper seeks to improve the empirical basis for theories that link population dynamics with aggregate change.

2 Heterogeneity and Aggregation in a Quality-Quantity Model

To shed light on how intergenerational shifts in population composition feed back into the process of fertility decline, this section studies a simple model in the tradition of the theoretical literature on demography and long-run economic growth. First, it derives how associations in the fertility behavior of parents and children aggregate up to the population level, irrespective of the specific behavioral model underlying these associations. Next, it analyzes a model in which parents of heterogeneous skill choose the quality and quantity of their children, using the earlier aggregation results to explore the evolving role of heterogeneity over the fertility transition. Finally, it broadens the discussion to consider whether the empirical implications change if factors outside the model also contribute to parent-child fertility associations.

2.1 Statistical Preliminaries

Let n_{it} denote the fertility of parent i from generation t, with mean μ_t and variance σ_t^2. Let $n_{i,t+1}$ denote the fertility (in adulthood) of each of the parent's children, such that if the parent has more than one child, then the $i, t+1$ subscript represents more than one member of generation $t+1$. Because the results below considers only expectations and conditional expectations, one can assume that siblings have the same fertility without loss of generality, so this slight abuse of notation is inconsequential. In fact, the model below exhibits no intra-family heterogeneity, but the results in this subsection are general and do not only apply to the model. Given the notation, parent i from generation t has $n_{it}n_{i,t+1}$ grandchildren.

The paper is interested in how the reweighting of the population due to differential fertility in generation t affects average fertility in generation $t+1$. To quantify this phenomenon:

Definition 1. The *composition effect* of differential fertility in generation t on average fertility in generation $t+1$, denoted Δ_{t+1}, equals the average fertility of generation $t+1$ minus the average number of grandchildren per child in generation t.

Using the notation above, one can express the composition effect as:

$$\begin{aligned}\Delta_{t+1} &= E_{t+1}\left[n_{i,t+1}\right] - E_t\left[E\left(n_{i,t+1}|n_{it}\right)\right] \\ &= E_t\left[\left(\frac{n_{it}}{\mu_t}\right)E\left(n_{i,t+1}|n_{it}\right)\right] - E_t\Big[E\left(n_{i,t+1}|n_{it}\right)\Big] \\ &= E_t\left[\left(\frac{n_{it}}{\mu_t}-1\right)E\left(n_{i,t+1}|n_{it}\right)\right]\end{aligned} \tag{1}$$

where $E_{t+1}\left[\cdot\right]$ is an expectation evaluated under the distribution of $n_{i,t+1}$; $E_t\left[\cdot\right]$ is an expectation evaluated under the distribution of n_t; and $E\left(n_{i,t+1}|n_{it}\right)$ is the conditional expectation of a child's fertility given her parent's fertility, also known as her childhood family size or sibship size. In the first term of the second line, the distribution of n_{it} is reweighted by the factor $\frac{n_{it}}{\mu_t}$ to give more weight to members of generation $t+1$ from larger sibships, reflecting the changing composition of the population from t to $t+1$. This factor gives more weight to members of generation $t+1$ from larger sibships. If the conditional expectation $E\left(n_{i,t+1}|n_{it}\right)$ is an increasing function, then the added weight given to larger families raises average fertility, so that $\Delta_{t+1} > 0$. In this case, fertility heterogeneity in generation t raises average fertility in generation $t+1$.

Both the model and the empirical work use a linear projection to summarize the conditional expectation function $E\left(n_{i,t+1}|n_{it}\right)$.

Definition 2. The *intergenerational fertility association*, denoted β_{t+1}, is the coefficient from the linear projection of $n_{i,t+1}$ on n_{it}.

This association has received much attention in the literature on the intergenerational transmission of behaviors, outcomes, and traits. Here, it is particularly convenient because it can simplify the formula for the composition effect. Because expression (3) represents the composition effect for a conditional expectation of any form, computation may prove complicated. With a linear conditional expectation, however, the expression reduces.

Lemma 1. *If $E\left(n_{i,t+1}|n_{it}\right)$ is linear, then $\Delta_{t+1} = \beta_{t+1}\frac{\sigma_t^2}{\mu_t}$.*

The Theory Appendix contains all proofs. This result will prove useful for both the theory and the empirical work. Δ_{t+1} increases in β_{t+1} and σ_t^2, while decreasing in μ_t. In other words, the composition effect of differential fertility is more positive when the intergenerational association is stronger or when the variance of childhood family size is larger relative to its mean. The role of the variance-to-mean ratio σ_t^2/μ_t, also known as the index of dispersion, in linking the cross-section with aggregate outcomes is not unique to the composition effect. Exactly the same ratio 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 differential fertility are larger when fertility is more dispersed relative to its mean.

Lemma 1 also provides a helpful decomposition of the composition effect in the linear case, which the empirical work will implement. One component measures similarity in the reproductive behavior of parents and children, while the other measures the relative spread of the fertility distribution among parents. Because the second component is always positive, the composition effect is negative—promoting fertility decline—only when the intergenerational association is negative.

2.2 Optimization Setup

The model setup closely follows the theoretical literature on differential fertility and economic growth.[6] Parents maximize a log-linear utility function over their own consumption c_{it}, the number of children n_{it}, and human capital per child $h_{i,t+1}$:

$$U\left(c_{it}, n_{it}, h_{i,t+1}\right) = \alpha \log\left(c_{it}\right) + (1-\alpha)\log\left(n_{it}h_{i,t+1}\right) \tag{2}$$

$\alpha \in (0,1)$ indexes the weight the parents place on their own consumption relative to the combined quantity and quality of children.

To produce child quality, or human capital, parents have access to a human capital production function that is isoelastic with respect to total inputs x_{it}: $h_{i,t+1} = x_{it}^{\eta}$, with $\eta \in (0,1)$. Each children is born with an input endowment $\theta > 0$ (reflecting basic human capacity or free public school), which parents can augment by purchasing additional education e_{it} at price p. The endowed and purchased inputs are assumed to be perfectly substitutable, so that $x_{it} = \theta + e_{it}$. One can view p as the inverse of the return to educational expenditure, so that an increase in this return is reflected in falling p. The presence of the input endowment implies that low-skill parents will choose a corner

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[6] See Galor and Moav (2002), Hazan and Berdugo (2002), de la Croix and Doepke (2003, 2005, 2008), and Moav (2005).

solution in which fertility rises with their human capital (de la Croix 2013; Vogl 2016), and also that the elasticity of human capital with respect to education is positive, which allows fertility to decline with parental human capital in the interior solution (Jones, Schoonbroodt, and Tertilt 2010). Parents themselves are endowed with human capital $h_{it} > 0$, drawn from an distribution F_t.

The aggregate production function is $Y_t = AH_t$, where $A > 0$ is the exogenous level of technology and H_t is the aggregate quantity of human capital in generation t, so the wage rate per unit of human capital is A. Notably, the aggregate and human capital productions function have one input each and are fixed over time. A fuller version of the model could incorporate spillovers, scale effects, and additional inputs, but this theory section seeks to shed light on the compositional mechanism and its empirical implications, not to provide a full theory of the growth process.

Each child costs $\tau \in (0, 1)$ units of time and $\kappa > 0$ goods, leading to the budget constraint:

$$c_{it} + \kappa n_{it} + pe_{it}n_{it} \leq Ah_{it} \left(1 - \tau n_{it}\right) \tag{3}$$

Parents spend their full income Ah_{it} on their own consumption (c_{it}), the quantity costs of children (κn_{it} and $\tau Ah_{it}n_t$), and the quality costs of children ($pe_{it}n_{it}$).

2.3 Optimization Results

The first order conditions imply that parents set education at:

$$e_{it} = \max \left\{ 0, \frac{1}{1-\eta} \left(\frac{\eta}{p} \left(Ah_{it}\tau + \kappa \right) - \theta \right) \right\} \tag{4}$$

Education starts at a corner solution of zero for low-skill parents and then rises linearly with parental skill in the interior solution. Parents spend on education if and only if their human capital exceeds $\widetilde{h} \equiv \frac{1}{\tau A} \left(\frac{p\theta}{\eta} - \kappa \right)$. This threshold also plays an important role in fertility choice:

$$n_{it} = \begin{cases} \frac{(1-\alpha)Ah_{it}}{\kappa + \tau Ah_{it}} & \text{if } h_{it} \leq \widetilde{h} \\ \frac{(1-\alpha)(1-\eta)Ah_{it}}{\kappa - p\theta + \tau Ah_{it}} & \text{if } h_{it} > \widetilde{h} \end{cases} \tag{5}$$

From inspection of equation (5), one can see that an additional assumption is necessary for unambiguous comparative statics with respect to parental skill.

Assumption 1. *The value of the input endowment is strictly larger than the goods cost:* $p\theta > \kappa$.

To obtain its value, the input endowment θ is scaled by the price of education p. This assumption guarantees that $\widetilde{h} > 0$, so parents with very low skill choose a corner solution, and also that the substitution effect of higher parental skill dominates its income effect in the interior solution.

Lemma 2. *Fertility* n_{it} *increases with parental human capital* h_{it} *over the interval* $(o, \widetilde{h}]$ *and decreases with* h_{it} *over the interval* $(\widetilde{h}, \infty)$.

Under Assumption 1, the model thus predicts a hump-shaped relationship between parental skill and fertility. Below $\widetilde{h}$, parents choose a corner solution for human capital expenditure, so the income effect of higher skill dominates the substitution effect, and fertility rises with skill. Above $\widetilde{h}$, the substitution effect dominates, so fertility declines with skill.[7] In data from 20 diverse developing countries, Vogl (2016) documents exactly this hump-shaped pattern, such that the least-skilled exhibit lower fertility in the early stages of development and higher fertility in the later stages.

The corner solution also generates an *s*-shaped relationship between the human capital of parents and children. Substitution of equation (4) into the human capital production function leads to a first-order, non-linear dynamical system $h_{i,t+1} = \phi(h_{it})$, where:

$$\phi\left(h_{it}\right) \equiv \begin{cases} \theta^{\eta} & \text{if } h_{it} \leq \widetilde{h} \\ \left\{ \left(\frac{\eta}{1-\eta}\right) \left(\frac{\kappa + \tau A h_{it}}{p} - \theta\right) \right\}^{\eta} & \text{if } h_{it} > \widetilde{h} \end{cases} \tag{6}$$

Equation (6) implies several useful properties.

Lemma 3. *The dynamical system* $\phi(\cdot)$ *is continuous, constant over the interval* $(o, \widetilde{h}]$, *and increasing and concave over the interval* $(\widetilde{h}, \infty)$, *with* $\lim_{h_{it} \to \infty} \phi'\left(h_{it}\right) = 0$.

These properties are key to identifying steady states of the dynamical system—with constant levels of human capital (and therefore fertility) across generations—which help shed light on the model's implications for intergenerational associations and composition effects over the fertility transition. In particular, $\phi(\cdot)$ may have multiple steady states, generating heterogeneity that is sufficiently tractable for the study of β_t and Δ_t.

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[7] If $p\theta \leq \kappa$, the declining portion of the hump disappears, so that fertility everywhere increases with parental skill.

Proposition 1. *The dynamical system $\phi(\cdot)$ is characterized by at least one and at most three steady state levels of human capital and fertility, of which at least one and at most two are stable.*

The dynamical system is guaranteed to have a steady state and may have up to three, two of which have positive human capital expenditure and one of which has none. Of these three steady states, those with the lowest and highest levels of human capital are stable, while the intermediate one (which exists only if one of the others also exist) is unstable. For an environment with three steady states, Figure 1 graphs the dynamical system together with the relationship between human capital and fertility. Steady states ss_1, ss_2, and ss_3 occur when $\phi(\cdot)$ intersects the 45-degree line. ss_1 and ss_3 are stable because $\phi(\cdot)$ crosses the 45-degree line from above, whereas ss_2 is unstable because it crosses from below. In this case, the fertility level associated with ss_1 is higher than that associated with ss_3, but other parameter values could lead to the opposite.

A more realistic version of the model could have idiosyncratic shocks to human capital, possibly leading to a steady state distribution of lineages, which contrasts the current model's indefinitely expanding mass points. In the presence of multiple lineage-specific steady states, different lineages expand at different rates, precluding a steady-state distribution but (perhaps attractively) implying long-run evolution, as in Galor and Moav (2002) and Galor and Michalopoulos (2012). The remainder of the section focuses on the two stable steady states of an environment with three steady states.

Definition 3. A *fertility regime* is a distribution of fertility in which all lineages are in stable steady states. A fertility regime is *non-degenerate* if fertility is heterogeneous within it.

The history of differential fertility over the course of economic development suggests two types of fertility regimes: one in which the higher-skill steady state has higher fertility, and one in which it has lower. I refer to the first type of regime as "Malthusian" and the second as "modern." In Figure 1, a population distributed across ss_1 and ss_3 would be in a modern fertility regime.

In this model, two forces are particularly natural for generating transitions between Malthusian and modern regimes: rising productivity and a rising return to human capital expenditure, as represented by a decrease in the price of education, p. Rising productivity pushes up the wage return to human capital, which increases fertility in the low-skill steady state, while decreasing fertility in the high-skill steady state. Falling p decreases the fertility of the high skilled, while leaving the low-skill steady state unchanged.

Proposition 2. *Consider a population initially in a non-degenerate fertility regime that experiences a one-time, permanent increase in A or decrease in p. If the population attains a new non-degenerate fertility regime, fertility in both the transition and the new regime is weakly higher among low human capital parents and strictly lower among high human capital parents.*

Consequently, if the population starts in a Malthusian regime, either force pushes it toward a modern regime. Each mechanism has a different implication for average fertility, however. A decline in p reduces average fertility in the population, while an increase in A has an ambiguous effect. In aggregate data on the demographic transition, average fertility typically first rises and then falls (Dyson and Murphy 1985), so both mechanisms are consistent with features of the historical fertility transition. The mechanisms directly relate to theories that place rising income and human capital at the center of the transition (Galor 2011), but they also capture theories involving new social norms that favor child investment (Caldwell 1981).

The model has omitted child mortality, which demographic transition theory views as a key driver of fertility change. Because child mortality occurs before substantial human capital investment, the model can capture it by dividing the quantity costs of children by the survival rate. If m is the child mortality rate, then the quantity costs become $\frac{\kappa}{1-m}$ and $\frac{\tau}{1-m}$. In this setup, a decrease in child mortality raises (surviving) fertility in both steady states, with ambiguous effects on fertility differentials. The prediction that net fertility rises with survival is common in fertility models in which a share m of children die deterministically, although Doepke (2004) finds that it also holds in appropriately parameterized models with stochastic child mortality and sequential fertility choice. Thus, in most macroeconomic models of the demographic transition, child mortality does not play a major role in net fertility change.

We are now equipped to consider how the intergenerational fertility association and the composition effect evolve over the transition from a Malthusian regime to a modern regime.

Proposition 3. *In any non-degenerate fertility regime and any transition between non-degenerate regimes, β_t and Δ_t are strictly positive, except during a transition from a Malthusian regime to a modern regime, during which they are weakly negative for a single generation.*

Because parents' human capital is positively associated with children's human capital, fertility is also positively associated in all pairs of generations except one: the generations on either side of a flip in fertility differentials by skill. In fact, because human capital and fertility are constant in a steady state, $\beta_t = 1$ within a fertility regime. This implication is quantitatively unrealistic but could be weakened by introducing stochastic shocks to human capital or income. As such, the model's predictions should be viewed as qualitative.

For population dynamics, the most important implication of Proposition 3 is that the composition effect is negative for a generation that experiences a reversal of differential fertility. If the reversal is contemporaneous with the onset of aggregate fertility decline, then the negative composition effect initially speeds the decline. In subsequent generations, however, the composition effect turns positive again, pushing back against aggregate fertility decline.

2.4 Empirical Implications

The most general empirical prediction is that when the fertility differential between high- and low-skill parents flips, the intergenerational fertility association and the composition effect turn negative for a generation. However, the model highlights only one source of the intergenerational association, human capital persistence. Other possible sources include the genetic heritability of fecundity and the cultural determinants of fertility preferences or behavior.[8] Behavioral genetics research finds some genetic heritability in markers of fecundity—including menstrual regularity and the ages at menarche and menopause (van Akker et al. 1987; Treloar and Martin 1990)—which may lead to the heritability of fertility. Meanwhile, a large literature in the social sciences highlights the role of culture in the intergenerational transmission of traits and behaviors. Sociologists (Duncan et al. 1965) have long emphasized this explanation for intergenerational fertility associations, positing that growing up in a large family shapes the preference for a large family of one's own.

To combine the model's prediction with these alternative sources of the intergenerational fertility association, one can express the association as:

$$\underbrace{\frac{dE\left[n_{t+1}|n_t\right]}{dn_t}}_{\text{overall association}} = \underbrace{\frac{\partial E\left[n_{t+1}|n_t, h_{t+1}\right]}{\partial n_t}}_{\text{net transmission}} + \underbrace{\frac{\partial E\left[n_{t+1}|n_t, h_{t+1}\right]}{\partial h_t}}_{\text{skill-fertility}} \times \underbrace{\frac{dE\left[h_{t+1}|n_t\right]}{dn_t}}_{\text{sibsize-skill}} \tag{7}$$

where the i subscripts are suppressed for simplicity. If the conditional expectation is linear, then

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[8] Intergenerational associations in other socioeconomic outcomes, such as income or health, may also play a role. Because these outcomes are closely linked to human capital, they are broadly related to the model.

$\beta_t = \frac{dE[n_{t+1}|n_t]}{dn_t}$. Ideally, one could derive structural expressions for these partial derivatives directly from the model, as in Becker and Tomes (1979), but the model's non-monotonicity implies that only reduced-form interpretations are possible.

Equation (7) expands the overall fertility association into sub-components using the chain rule. These subcomponents include any intergenerational transmission of fertility net of the human capital mechanism, $\frac{\partial E[n_{t+1}|n_t,h_{t+1}]}{\partial n_t}$; the relationship between skill and fertility, $\frac{\partial E[n_{t+1}|n_t,h_{t+1}]}{\partial h_t}$; and the relationship between childhood family size and skill, $\frac{\partial E[h_{t+1}|n_t]}{\partial n_t}$. The first sub-component captures persistence in the determinants of fertility that are not correlated with education, perhaps genetics or culture. The model focuses on the second and third sub-components, which change in a staggered fashion during the demographic transition. In a Malthusian regime, higher-skill parents bear more children, so $\frac{\partial E[n_{t+1}|n_t,h_{t+1}]}{\partial n_t} > 0$, and women from larger sibships obtain more education, so $\frac{dE[h_{t+1}|n_t]}{dn_t} > 0$. In a modern regime, both patterns are flipped, so $\frac{\partial E[n_{t+1}|n_t,h_{t+1}]}{\partial n_t} < 0$ and $\frac{dE[h_{t+1}|n_t]}{dn_t} < 0$. In the transition between these two regimes, a single generation experiences long and auxiliary parameters of opposite sign: $\frac{\partial E[n_{t+1}|n_t,h_{t+1}]}{\partial n_t} < 0$ and $\frac{dE[h_{t+1}|n_t]}{dn_t} > 0$. If the net intergenerational transmission component is small or varies little over time, then the intergenerational association $\frac{dE[n_{t+1}|n_t]}{dn_t}$ follows the trajectory predicted by the model: large within the Malthusian and modern regimes, small during the transition between them. However, in the presence of net intergenerational transmission, $\frac{dE[n_{t+1}|n_t]}{dn_t}$ may not turn negative in the transition. Figure 2 represents these changes schematically by plotting $\frac{dE[n_{t+1}|n_t]}{dn_t}$ against $\frac{\partial E[h_{t+1}|n_t]}{\partial n_t}$ across the different fertility regimes.

Given Lemma 1, equation (7) has similar implications for the composition effect. The composition effect will be positive within the Malthusian and modern regimes but will shrink and possibly turn negative during the transition. If it does turn negative during the transition, then it will initially speed the process of fertility decline, as predicted by the model. Otherwise, fertility will never decline faster than it would in the absence of population reweighting, but in either case, the subsequent growth of the composition effect will slow the process of fertility decline.

The paper will argue that in the postwar era, developing countries moved from the transition generation to the modern regime. The results will show that the intergenerational association and the composition effect grew as the relationship between education and sibship size flipped from positive to negative. Because this reversal coincided with fertility decline (Vogl 2016), one can expect the intergenerational association and the composition effect to grow as aggregate fertility falls.

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, while 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 behavior in a lineage over two generations.

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.[9] 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 Appendix Table 1 for a list of countries and survey years).[10] 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 strategy 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. Notably, this approach abstracts from the model, which considers generations, or all women born to the same group of mothers. Each cohort statistic characterizes a *hypothetical* generation of families whose size is distributed according to the cross-sectional distribution of sibship size in the birth cohort.

Analyses of both 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. If a country-cohort cell includes data from surveys $k = 1, \cdots, K$, each with N_k observations, then the weights from survey k are

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

[10] 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.

rescaled to sum to $\frac{N_k}{\sum_k N_k}$. This approach weights surveys in proportion to their contribution to the country-cohort sample. In the second step, analyses are unweighted to ensure representativeness. For precision, I drop cells smaller than 250 women, the 5^{th} 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, while the second step randomly draws countries.[11] I do not otherwise correct for estimation error in the cell-level parameter estimates; earlier work on the same dataset (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. For completeness, it reports results for both ever-born and surviving fertility. Ever-born fertility is more relevant for intergenerational associations in fertility *behavior*, whereas surviving fertility is more relevant for intergenerational associations in fertility *outcomes*. Either measure of fertility may be relevant for the *demand for children*, depending on parents' ability to target the number of surviving offspring subject to mortality risk.[12]

4.1 Methods

I estimate intergenerational associations using a linear 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:

$$y^a_{ict} = \alpha^a_{ct} + \beta^a_{ct} s_{ict} + u^a_{ict} \tag{8}$$

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

[12] From the model's perspective (and an evolutionary perspective), only surviving fertility is relevant. Surviving fertility is also attractive because it is less subject to recall bias, or the forgetting of deceased children.

where y_{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. It is not a causal effect, and its sources are not necessarily limited to the mechanism specified in the model.

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, while 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 (Solon and Haider 2006).[13] In a recent analysis, 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.

Along these lines, I choose the earliest age a for which β_{ct}^a approximates the completed fertility transmission coefficient. To find this age, 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 the cohort's age-45 association on its association at an earlier age.[14] Appendix Figure 1 plots the results by age, 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 significantly different from zero and extremely close to 1 for ever-born and surviving fertility. At age 20, however, the estimated slope for surviving fertility is substantially (albeit insignificantly) below 1 and also not significantly different from 0. Given these results, the analysis focuses on cumulative fertility at age 25.

Motivated by equation (7), one can decompose the intergenerational fertility association into its driving forces: (1) the association of sibship size and fertility, conditional on human capital; (2) the association of human capital and fertility, conditional on sibship size; and (3) the association of sibship size and human capital. Two equations summarize these three partial derivatives. The first expresses fertility outcomes as a function of sibship size and education:

$$y_{ict}^a = \mathrm{A}_{ct}^a + \mathrm{B}_{ct}^a s_{ict} + \Gamma_{ct}^a edu_{ict} + U_{ict}^a \tag{9}$$

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[13] 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).

[14] A limitation of this approach is that it overlooks future changes in the age profile of fertility.

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

$$edu_{ict} = \psi_{ct} + \varphi_{ct} s_{ict} + v_{ict} \tag{10}$$

In the language Goldberger (1991) uses to characterize omitted variables bias, equation (8) is a "short" regression, while equations (9) and (10) are the corresponding "long" and "auxiliary" regressions. B^a_{ct} is the net intergenerational transmission term discussed in Section 2.4, accounting for factors outside the theoretical framework. Γ^a_{ct} is the skill-fertility association, representing differential fertility in the current generation, while φ_{ct} is the sibsize-skill association, reflecting differential fertility in the last generation. By equation (7), the cohort coefficients are related by the identity $\beta^a_{ct} = \mathrm{B}^a_{ct} + \varphi_{ct}\Gamma^a_{ct}$, which confirms that β^a_{ct} is smaller when Γ^a_{ct} 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, a period in 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.

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 1945-54 to 1975-83 (data are unavailable for 1984), the table estimates the four slope parameters of equations (8)-(10) using age-25 ever-born fertility. Panel A reports estimates of the overall intergenerational fertility association, β^a_{ct}, which is 0 in the 1945-54 cohort but steadily grows to a statistically significant 0.08 by the 1975-83 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 an 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 modern 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 Malthusian to modern fertility 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.

Distribution of Parameter Estimates The full-sample analysis applies these same methods to all 5-year birth 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 immediately emerge for intergenerational associations in both ever-born and surviving fertility. First, the central tendencies of β^a_{ct} and B^a_{ct} are close to zero, and the supports of their distributions contain both positive and negative values. Second, the dispersion of B^a_{ct}—from the "long" regression, which controls for education—is smaller than that of β^a_{ct} 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, Appendix Figure 2 plots kernel densities of the estimated β^a_{ct} and B^a_{ct} across country-cohort cells, revealing that the distribution of B^a_{ct} has shorter right *and* left tails than the distribution of β^a_{ct}. 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 Figure 2 are the result of sampling variability. However, the distributions of *t*-statistics in Table 2 do not fit such an interpretation. At the 5 percent significance level, the ever-born fertility association is significantly positive in 29 percent of cells and significantly negative in 2 percent; the surviving fertility association is significantly positive in 16 percent of cells and significantly negative in 9 percent. As a result, 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 percent of the estimates significantly negative for ever-born fertility and 80 percent 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 percent of φ_{ct} estimates are significantly positive and 26 percent negative. For surviving fertility, 56 percent are positive and 16 percent negative.

Cohort Trends in Parameter Estimates The preceding evidence suggests that most women in the sample bore children during the modern era, but some were born during the Malthusian era. 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 the the only cohort for which data are available for all countries, 1965-9, 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 1965-9 mean; the point estimates and 95 percent confidence intervals are for differences relative to this line.

Starting from the right-hand side of Figure 3, one can see clear evidence of the transition from Malthusian to modern regimes. For both ever-born and surviving sibship size, the sibsize-skill association is positive on average for the 1965-9 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 1965-9 cohort, but similar to the sibsize-skill association, it is significantly more positive 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 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 1965-9 cohort. Magnitudes are not large: the intergenerational association averages 0.02-0.03 for the 1980-4 cohort, implying that a woman with 10 siblings can expect to have $\frac{1}{10}$ 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.

Relationship Between Parameter Estimates While 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 non-parametric 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 $\frac{1}{3}$ fewer children than her counterpart without siblings. The intercepts of the local linear regressions are significantly positive at the 5 percent level, reflecting a net transmission coefficient B_{ct}^{a} that is on average greater than zero. As reported in the top-right corners of the figures, ordinary least squares (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 estimated sibsize-education association explains roughly one-third of the variation in the estimated intergenerational fertility association.

Despite the apparent importance of regional variation, within-country variation produces similar results. The right-hand side of Figure 3 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 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 percent level.

Role of Marriage and Fertility Onset The fact that intergenerational fertility associations measured early in the reproductive lifecycle strongly predict associations measured late in the reproductive lifecycle suggests that marriage and the initiation of childbearing may play an important role. To what extent do the preceding results reflect changes in the ages at marriage and first birth? Ordinary least squares estimation of equation (8) is inappropriate for answering this question because never-married and childless women have censored outcomes. As such, I estimate Cox hazard regressions in which the age at first marriage or first birth is the outcome, and surviving sibship size is the independent variable.[15]

Figure 5 presents the results in a format analogous to Figure 4, plotting the hazard ratio against the sibsize-skill association on the left-hand side, and plotting residuals net of country and cohort fixed effects on the right-hand side. A hazard ratio greater (less) than 1 indicates that women from larger sibships have higher (lower) marriage or first birth risk. For both outcomes, both with and without country and cohort fixed effects, Figure 5 reveals clear negative slopes. When women with more siblings obtain more education, they marry and begin having children later, as reflected in hazard ratios that are on average significantly below 1. In contrast, when such women obtain less education, they marry and begin having children earlier, as reflected in hazard ratios that are on average significantly above 1. The explanation for this pattern follows the same logic as that for Figure 4. Most women in the sample came of age in an era when more education meant later marriage and birth. As a result, for those born in the Malthusian era, sibship size negatively predicts marriage and childbearing risk, while for those born in the modern era, the opposite result obtains.

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[15] Results for ever-born sibship size are similar, so I omit them to conserve space.

Aggregate Predictors of the Intergenerational Fertility Association The theoretical framework showed that human capital can play an important role in the evolution of the intergenerational fertility association. One way to test this proposition is to relate the association to economic and demographic aggregates. To this end, this section regresses the intergenerational fertility association on log GDP per capita (from the Penn World Table), the urbanization rate (from the UN), the infant mortality rate (from the UN), and average educational attainment among adults (from the Barro and Lee dataset). Because the intergenerational association depends on fertility decisions in two generations, I consider two measurements of each variable, first in the five-year period of birth and then in the five-year period surrounding the 20^{th} birthday.

Table 3 reports the results, with ever-born fertility in columns (1)-(4) and surviving fertility in columns (5)-(8). The odd-numbered columns only include aggregates measured at birth; the even-numbered columns add the age-20 measures. Because the aggregate data are not available for the full panel, the sample size shrinks to 150 country-cohort cells. All regressions include country and cohort fixed effects, standard errors are clustered at the country level.

Columns (1) and (5) begin with all four aggregate variables measured in childhood, finding a significant role for education but not living standards, urbanization, or infant mortality. For both ever-born and surviving fertility, a one-year increase in average educational attainment is associated with a strengthening of the intergenerational association by slightly more than 0.02, or two-thirds of a standard deviation. Adding the age-20 measures in columns (2) and (6) does not change the takeaway, with significant coefficients on the education variables but no others. The coefficient on average education at birth shrinks somewhat, implying that some of the relationship between average education at birth and the intergenerational fertility association is mediated by average education in early adulthood. However, the two fertility measures yield conflicting results on which age is more important.

Because changes in living standards, urbanization, and infant mortality appear to play no role in the evolution of the intergenerational fertility association, it is useful to rerun the preceding regressions omitting these covariates. Columns (3)-(4) and (7)-(8) carry out this exercise, regression the estimated association on average education in childhood and early adulthood, plus country and cohort fixed effects. The results are similar but generally more statistically significant.[16]

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[16] In columns (3)-(4) and (7)-(8), it is possible to expand the sample because data on GDP per capita are sparse. In the

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 model 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.[17] 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 definition of the composition effect I take to the data must involve two ingredients: the average fertility of women from cohort ct, $\bar{y}^a_{ct}$, and their deweighted average fertility, $\tilde{y}^a_{ct}$, 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 $\bar{y}^a_{ctk}$ be the average fertility of women with k surviving females in their sibships. Then:

$$\bar{y}^a_{ct} = \textstyle\sum_{k=1}^{K} \eta_{ctk}\bar{y}^a_{ctk} \qquad \text{and} \qquad \tilde{y}^a_{ct} = \textstyle\sum_{k=1}^{K} \left(\frac{\eta_{ctk}/k}{\sum_{l=1}^{K} \eta_{ctl}/l}\right) \bar{y}^a_{ctk}$$

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

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expanded sample, the results for education remain similar but again become more statistically significant.

[17] 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.

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

$$\delta_{ct}^{a} = \frac{\bar{y}_{ct}^{a} - \tilde{y}_{ct}^{a}}{\tilde{y}_{ct}^{a}} \tag{11}$$

This expression is a simple non-linear combination of the weighted and deweighted averages. The non-parametric 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, $\tilde{y}_{ct}^{a}$ reweights on the number of *surviving* sisters only, as deceased sisters are irrelevant to the 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. 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.[18] For county-cohort ct, the decomposition is:

$$\delta_{ct}^{a} = \left(\frac{\beta_{ct}}{\tilde{y}_{ct}}\right)\left(\frac{\tilde{\sigma}_{ct}^{2}}{\tilde{s}_{ct}}\right) \tag{12}$$

where β_{ct} is the slope from a regression of ever-born fertility on surviving sibship size; $\tilde{y}_{ct}$ is defined above; and $\tilde{\sigma}_{ct}^{2}$ and $\tilde{s}_{ct}$ 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 for 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.

Bolivian Case Study The case study of Bolivia appears again in Table 4, using the same four decadal cohorts as Table 1. Panel A presents relative composition effects across cohorts, estimated

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[18] 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.

first non-parametrically using equation (11) and then parametrically using equation (12). Panel B then decomposes each parametric estimate into a relative fertility association and a variance-to-mean ratio. Panel C reports additional descriptive statistics. Because the estimands in Panels A and B are non-linear combinations of other parameters, standard errors are block-bootstrapped at the primary sampling unit level.

In Panel A, both the non-parametric and parametric estimates are consistent with a population that started in transition and then settled into a modern 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 percent. The non-parametric 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 percent. 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 versus 1.8 children ever born) but ends lower (1.5 versus 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 sibling is associated with a 6 percent 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 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.

Composition Effects over the Fertility Transition For the full sample, Figure 6 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 $(1+\delta)\,x$ when deweighted fertility is x.

On the left side of Panel A, non-parametric estimates of equation (11) 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 as much as 10 percent, and by 4 percent on average—with the regression function significantly different from zero at $p = 0.06$. OLS estimation on this scatterplot yields a marginally significant negative slope coefficient of -0.010 ($p = 0.13$).[19] 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 thus higher at lower levels of cohort fertility.

On the right side of Panel A, parametric estimates based on equation (12) point to a similar but even more pronounced rise below 1.5. At the 5 percent 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 6 decompose equation (12) 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 percent level. The results for the full sample thus mimic the case study evidence from Bolivia.

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

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[19] With the inclusion of country and cohort fixed effects, the coefficient on the continuous measure rises in absolute value, to -0.019, but maintains a similar significance level, at $p = 0.16$.

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, redefine the outcome y_{ict}^{a} as an 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 $\bar{y}_{ct}^{a}$ is an age-specific fertility rate for age a in year $\tau = t + a$. Similarly, the deweighted cohort average $\tilde{y}_{ct}^{a}$ 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:

$$TFR_{c\tau} = 5\textstyle\sum_a \bar{y}_{c,\tau-a}^{a} \qquad \text{and} \qquad dTFR_{c\tau} = 5\textstyle\sum_a \tilde{y}_{c,\tau-a}^{a}$$

The summations are multiplied by five because I use five-year age groups, from 15-19 to 45-49.[20] 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:

$$\delta_{c\tau} = \frac{TFR_{c\tau} - dTFR_{c\tau}}{dTFR_{c\tau}} \tag{13}$$

As in the cohort analysis, this expression is a non-linear combination of weighted and deweighted averages. The empirical analog is a non-parametric 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 (13) 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:

$$\delta_{c\tau} = \frac{\sum_a \beta_{c,\tau-a}^{a} \frac{\sigma_{c,\tau-a}^{2}}{\mu_{c,\tau-a}}}{dTFR_{c\tau}} \approx \left(\frac{5\sum_a \beta_{c,\tau-a}^{a}}{dTFR}\right) \left(\frac{1}{7}\sum_a \frac{\tilde{\sigma}_{c,\tau-a}^{2}}{\tilde{\mu}_{c,\tau-a}}\right) \tag{14}$$

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[20] Specifically, for age group a with lower bound $\underline{a}$ and upper bound $\overline{a}$, the birth cohort $\tau - a$ would be born between the year $\tau - \underline{a}$ and the year $\tau - \overline{a}$.

where $\beta^a_{c,\tau-a}$ 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, while $\tilde{\sigma}^2_{c,\tau-a}$ and $\tilde{\mu}_{c,\tau-a}$ are the deweighted variance and mean of sibship size, respectively. In the approximate decomposition of equation (14), $\delta_{c\tau}$ again has two parts: a relative association and a ratio. In the first, the total fertility association $5\sum_a \beta^a_{c,\tau-a}$, 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 in the linear case.

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 7 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, non-parametric 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 percent on average ($p < 0.01$), and by as much as 6 percent. OLS estimates also show a significantly negative slope, 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 (14) 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 implied evolution of the composition effect over the fertility transition. As deweighted TFR falls below 4 in Panel B of Figure 7, 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 percent 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, then, the analysis of period fertility rates has similar conclusions to the analysis of cohort fertility rates. In the later phases of the process of aggregate fertility decline, the composition effect slows the process by raising average fertility. With non-parametric estimates of 4 percent on average and 6-10 percent in the most pronounced cases, these results explain a small but systematic feature of aggregate fertility dynamics.

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.

First, it first theoretically explores the evolution of the association in a quality-quantity framework drawn from the literature on demography and long-run economic growth. The theoretical results highlight the importance of the changing relationship between human capital and fertility. Intergenerational fertility associations—and therefore also composition effects—turn positive when fertility differentials by skill are aligned across generations, which occurs within the Malthusian or modern regimes but not during the transition between them. 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 during the transition to a modern fertility regime, as the link between human capital and fertility flips from positive to negative, and the skill-fertility association becomes more 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 2012). 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).

While 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, and especially to the recent "stalls" Bongaarts (2006, 2008) has identified in many populations. 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 micro-level demographic phenomena influencing the pace of aggregate change.

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Theory Appendix

Proof of Lemma 1

Let $E\left(n_{i,t+1}|n_{it}\right) \equiv a + bn_{it}$. Then:

$$\begin{aligned}
\Delta_{t+1} &= E_t\left[\left(\frac{n_{it}}{\mu_t}\right)E\left(n_{i,t+1}|n_{it}\right)\right] - E_t\Big[E\left(n_{i,t+1}|n_{it}\right)\Big] \\
&= E_t\left[\left(\frac{n_{it}}{\mu_t}\right)\left(a + bn_{it}\right)\right] - E_t\Big[a + bn_{it}\Big] \\
&= \frac{b}{\mu_t}E_t\left[n_{it}^2\right] - bE_t\Big[n_{it}\Big] \\
&= b\frac{E_t\left[n_{it}^2\right] - bE_t\Big[n_{it}\Big]^2}{\mu_t} \\
&= b\frac{\sigma_t^2}{\mu_t}
\end{aligned}$$

Since β_{t+1} is the coefficient from the linear projection of $n_{i,t+1}$ on n_{it}, $\beta_{t+1} = b$. Then $\Delta_{t+1} = \beta_{t+1}\frac{\sigma_t^2}{\mu_t}$.

Proof of Lemma 2

Differentiation of equation (5) leads to:

$$\frac{\partial n_{it}}{\partial h_{it}} = \begin{cases} \frac{(1-\alpha)\kappa A}{\left(\kappa+\tau A h_{it}\right)^2} > 0 & \text{if } h_{it} \leq \widetilde{h} \\ \frac{(1-\alpha)(1-\eta)(\kappa-p\theta)A}{\left(\kappa-p\theta+\tau A h_{it}\right)^2} < 0 & \text{if } h_{it} > \widetilde{h} \end{cases}$$

Proof of Lemma 3

$\phi\left(\cdot\right)$ has domain $\mathbb{R}_+$, is a constant function for $h_{it} < \widetilde{h}$, and is a power function for $h_{it} > \widetilde{h}$, implying continuity for all $h_{it} \neq \widetilde{h}$. Further, $\lim_{h_{it}\downarrow\widetilde{h}}\left\{\left(\frac{\eta}{1-\eta}\right)\left(\frac{\kappa+\tau A h_{it}}{p} - \theta\right)\right\}^{\eta} = \theta^{\eta}$, proving continuity on $\mathbb{R}_+$. Differentiation of equation (6) leads to:

$$\phi'\left(h_{it}\right) = \begin{cases} 0 & \text{if } h_{it} \leq \widetilde{h} \\ \eta\left(\frac{\tau A}{p}\right)\left(\frac{\eta}{1-\eta}\right)^{\eta}\left(\frac{\kappa+\tau A h_{it}}{p} - \theta\right)^{\eta-1} > 0 & \text{if } h_{it} > \widetilde{h} \end{cases}$$

where the second line is positive because $\frac{\kappa+\tau A h_{it}}{p} - \theta > \frac{\kappa+\tau A\widetilde{h}}{p} - \theta = \theta\left(\frac{1}{\eta} - 1\right) > 0$. In the limit, $\lim_{h_{it}\to\infty}\phi'\left(h_{it}\right) = \lim_{h_{it}\to\infty}\eta\left(\frac{\tau A}{p}\right)\left(\frac{\eta}{1-\eta}\right)^{\eta}\left(\frac{\kappa+\tau A h_{it}}{p} - \theta\right)^{\eta-1} = 0$.

Further differentiation leads to:

$$\phi''\left(h_{it}\right)=\begin{cases}0 & \text{if } h_{it}\leq\widetilde{h}\\ \eta\left(\eta-1\right)\left(\frac{\tau A}{p}\right)^{2}\left(\frac{\eta}{1-\eta}\right)^{\eta}\left(\frac{\kappa+\tau Ah_{it}}{p}-\theta\right)^{\eta-2}<0 & \text{if } h_{it}>\widetilde{h}\end{cases}$$

Proof of Proposition 1

To prove that at least one steady state exists, note:

- If $\widetilde{h}>\theta^{\eta}$, then $\phi\left(\cdot\right)$ must cross the 45 degree line from above at $h_{it}=\theta^{\eta}$ because $\phi\left(h_{it}\right)=\theta^{\eta}$ for all $h_{it}\leq\widetilde{h}$.
- If $\widetilde{h}\leq\theta^{\eta}$, then $\phi\left(\cdot\right)$ must cross the 45 degree line from above at some $h_{it}>\theta^{\eta}$ because $\phi\left(\cdot\right)$ is continuous, $\phi\left(\theta^{\eta}\right)>\theta^{\eta}$, and $\lim_{h_{it}\to\infty}\phi'\left(h_{it}\right)=0$.

In each of these steady states, $\phi\left(\cdot\right)$ crosses the 45 degree line from above, so at least one steady state is stable. To prove that the number of steady states cannot exceed three, note:

- For $h_{it}>\widetilde{h}$, $\phi\left(\cdot\right)$ is strictly increasing and strictly concave, so it can cross or be tangent to the 45 degree line at most twice, once from below with $\phi'>1$ and once from above with $\phi'<1$.
- For $h_{it}\leq\widetilde{h}$, $\phi\left(\cdot\right)$ is constant, so it can cross the 45 degree line from above or be tangent to it only once.

Because $\phi\left(\cdot\right)$ can cross the 45 degree line from above at most once for $h_{it}>\widetilde{h}$ and at most once for $h_{it}\leq\widetilde{h}$, at most two steady states are stable.

Proof of Proposition 2

An increase in A or decrease in p reduces the corner solution threshold $\frac{1}{\tau A}\left(\frac{p\theta}{\eta}-\kappa\right)$. Call this threshold $\hat{h}$, so that $\hat{h}<\widetilde{h}$. Then differentiation of equation (5) leads to:

$$\frac{\partial n_{it}}{\partial A}=\begin{cases}\frac{(1-\alpha)\kappa h_{it}}{(\kappa+\tau Ah_{it})^{2}}>0 & \text{if } h_{it}\leq\hat{h}\\ \frac{(1-\alpha)(1-\eta)h_{it}(\kappa-p\theta)}{(\kappa-p\theta+\tau Ah_{it})^{2}}<0 & \text{if } h_{it}>\widetilde{h}\end{cases}$$

and:

$$\frac{\partial n_{it}}{\partial p}=\begin{cases}0 & \text{if } h_{it}\leq\hat{h}\\ \frac{\theta(1-\alpha)(1-\eta)Ah_{it}}{(\kappa-p\theta+\tau Ah_{it})^{2}}>0 & \text{if } h_{it}>\widetilde{h}\end{cases}$$

Differentiation of equation (6) leads to:

$$\frac{\partial \phi}{\partial A} \equiv \begin{cases} 0 & \text{if } h_{it} \leq \hat{h} \\ \left(\frac{\eta}{1-\eta}\right)^{\eta} \left(\frac{\kappa+\tau A h_{it}}{p} - \theta\right)^{\eta-1} \frac{\eta \tau h_{it}}{p} > 0 & \text{if } h_{it} > \widetilde{h} \end{cases}$$

and:

$$\frac{\partial \phi}{\partial p} \equiv \begin{cases} 0 & \text{if } h_{it} \leq \hat{h} \\ -\frac{\eta}{p} \left(\frac{\eta}{1-\eta}\right)^{\eta} \left(\frac{\kappa+\tau A h_{it}}{p} - \theta\right)^{\eta-1} \left(\frac{\kappa+\tau A h_{it}}{p}\right) < 0 & \text{if } h_{it} > \widetilde{h} \end{cases}$$

First consider lineages initially in the low human capital stable steady state, $h_{it} = \theta^{\sigma}$. Since the population attains a new non-degenerate fertility regime, $\hat{h} > \theta^{\eta}$. Thus, for these lineages, $\phi(\cdot)$ and therefore h_{it} do not change. In the case of higher A, these lineages choose higher n_{it}; in the case of lower p, n_{it} is unchanged.

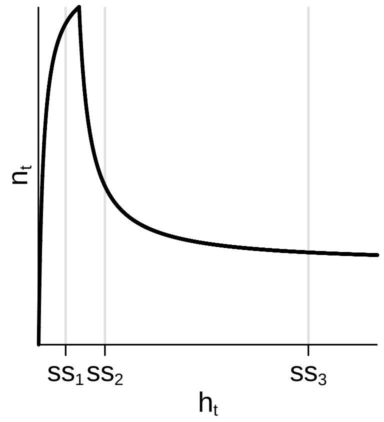
Next consider lineages initially in the high human capital stable steady state, with $h_{it} > \widetilde{h}$. $\phi(\cdot)$ rises from higher A or lower p, so h_{it} rises with t, and $h_{it} > \widetilde{h}$ in every period. Holding h_{it} constant, n_{it} falls from higher A and lower p. Since h_{it} rises with t and $\frac{\partial n_{it}}{\partial h_{it}} < 0$ for $h_{it} > \widetilde{h}$, n_{it} falls further. Thus, for these lineages, n_{it} is lower in the transition and the new regime.

Proof of Proposition 3

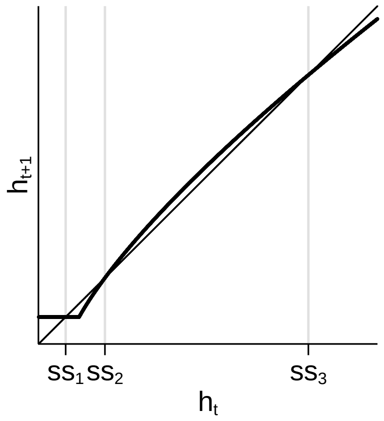
Denote the stable steady state human capital levels in generation t as h_{0t} and h_{1t}, with $h_{0t} < h_{1t}$, and let n_{0t} and n_{1t} denote the associated fertility levels. Let $h_{0,t+1}$, $h_{1,t+1}$, $n_{0,t+1}$, and $n_{1,t+1}$ be the same outcomes for the next generation of the 0 and 1 lineages. Then the intergenerational transmission coefficient is $\beta_{t+1} = \frac{n_{1,t+1} - n_{0,t+1}}{n_{1t} - n_{0t}}$. If the child cost parameters and the human capital production function is the same in both t and $t+1$, then $h_{i,t+1} = h_{it}$ and $n_{i,t+1} = n_{it}$ for all lineages, so $\beta_{t+1} = 1$. In the transition between two Malthusian regimes, $n_{0t} < n_{1t}$, $n_{0,t+1} < n_{1,t+1}$, $n_{0,t+1} \geq n_{0t}$, and $n_{1,t+1} < n_{1t}$, so $\beta_{t+1} \in (0,1)$. In the transition between two modern regimes, $n_{0t} > n_{1t}$, $n_{0,t+1} > n_{1,t+1}$, $n_{0,t+1} \geq n_{0t}$, and $n_{1,t+1} < n_{1t}$, so $\beta > 1$. During a transition between Malthusian and modern regimes, there exists t such $n_{0t} > n_{1t}$, $n_{0,t+1} \leq n_{1,t+1}$, $n_{0,t+1} \geq n_{0t}$, and $n_{1,t+1} < n_{1t}$, so $\beta_{t+1} \leq 0$. Because the skill distribution has two mass points in any non-degenerate regime and any transition between non-degenerate regimes, $E(n_{t+1}|n_t)$ can be fully characterized by a linear function, and $\sigma_t^2 > 0$. Therefore, $\Delta_{t+1} = \beta_{t+1} \frac{\sigma_t^2}{\mu_t}$. Since $\mu_t > 0$, $\text{sgn}(\Delta_{t+1}) = \text{sgn}(\beta_{t+1})$.

Figure 1: Fertility and the Dynamics of Human Capital

A. Optimal fertility

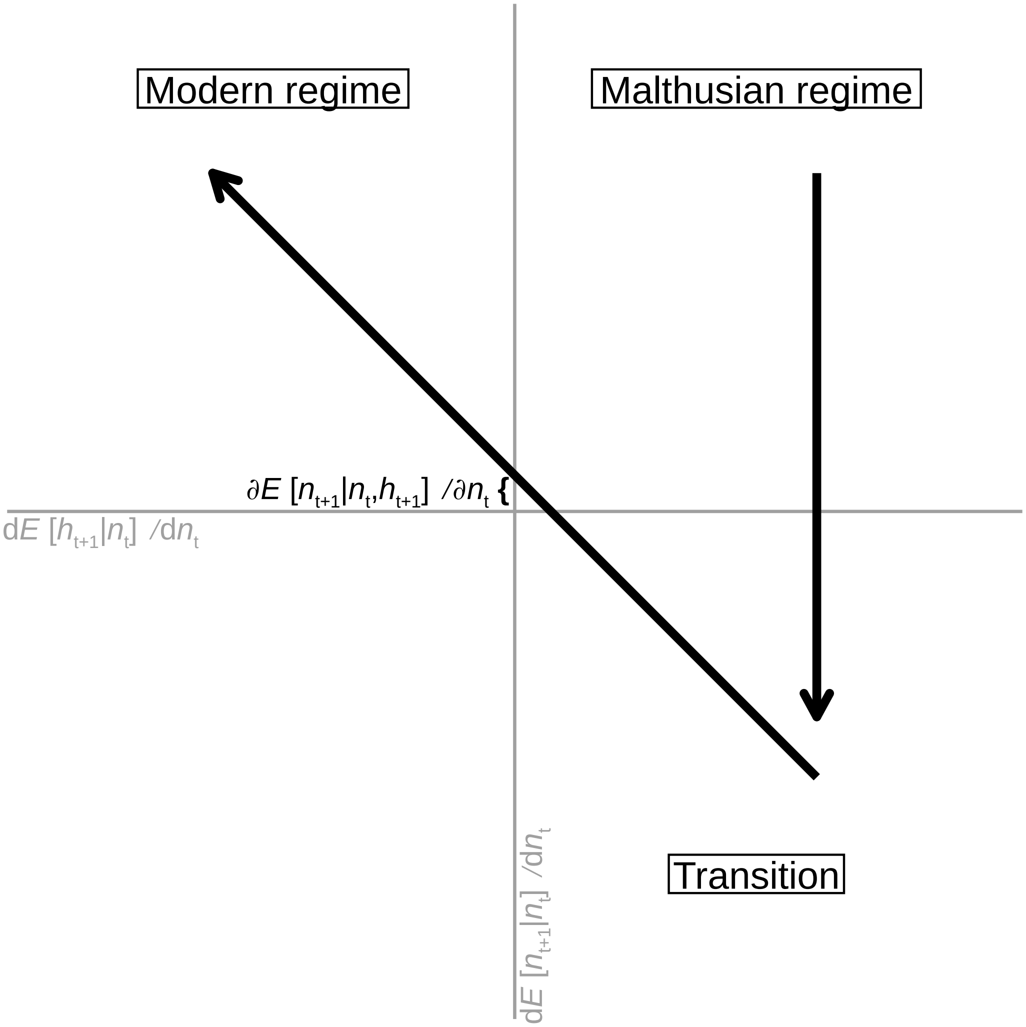


B. Dynamical system



Note: The figures depict a parameterization of the model in which steady states with higher human capital have lower fertility. A modern fertility regime would obtain if all lineages were located at ss_1 or ss_3.

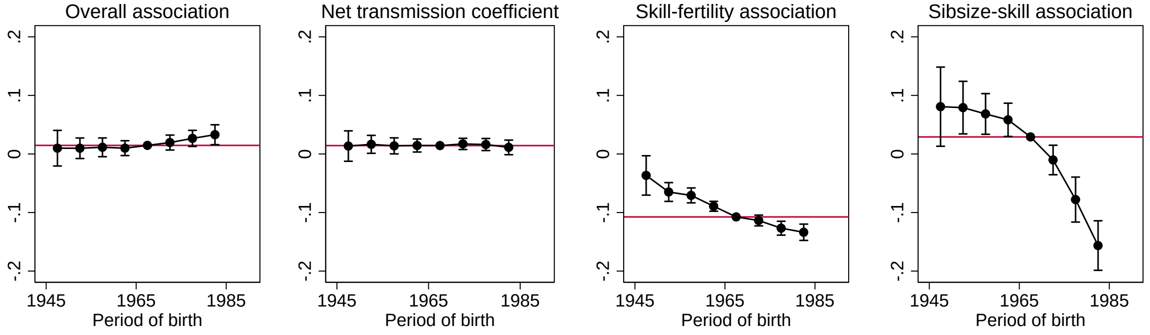
Figure 2: Intergenerational Associations across Fertility Regimes



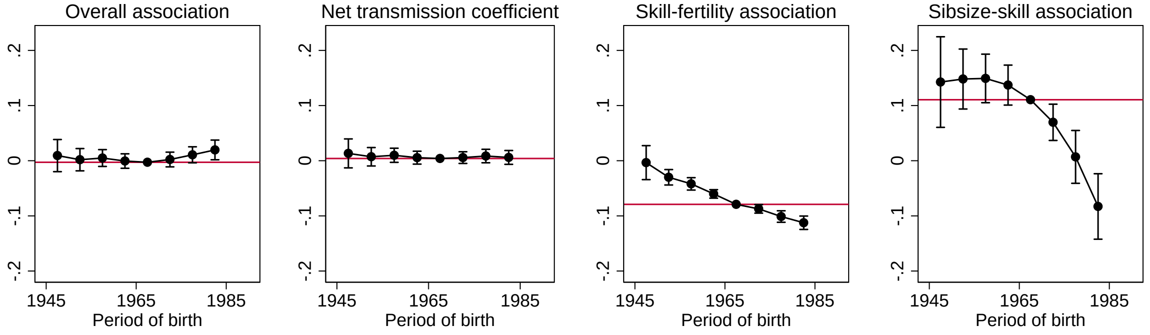
Note: The figure is a schematic plot of the overall intergenerational fertility association against the sibsize-skill relationship. In the Malthusian regime, the sibsize-skill and skill-fertility relationships are both positive, leading to a positive intergenerational fertility association. In the transition, the sibsize-skill relationship stays positive, but the skill-fertility relationship turns negative, leading to a potentially negative intergenerational fertility association. In the modern regime, the sibsize-skill and skill-fertility relationships are both negative, leading to a positive intergenerational fertility association. The intercept reflects the net intergenerational transmission coefficient.

Figure 3: Cohort Effects in Parameter Estimates

A. Ever-born

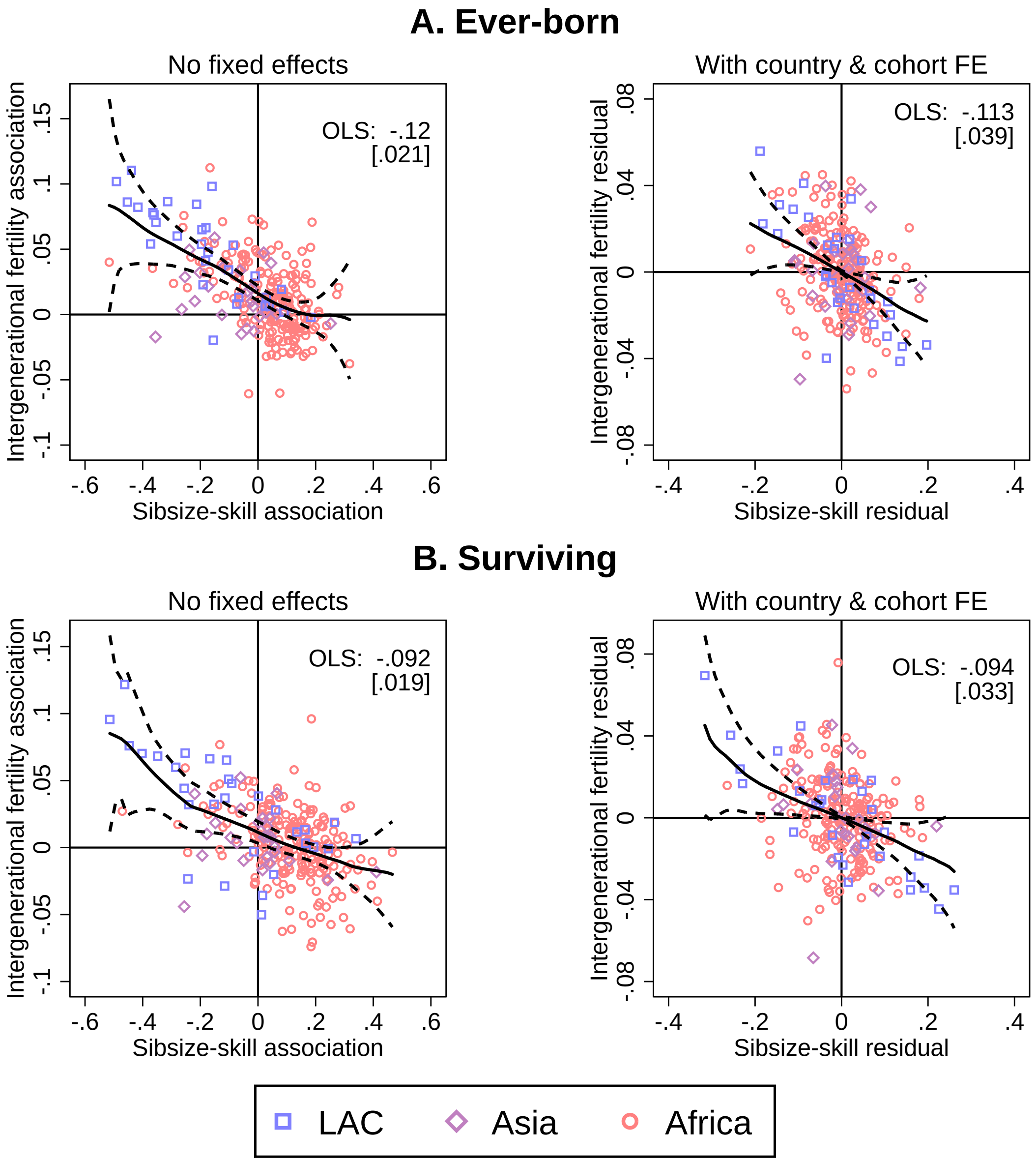


B. Surviving



Note: 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 1965-69, the only cohort with data available from all countries. Horizontal lines are average parameter values across countries for the 1965-69 cohort. Fertility associations are based on cumulative fertility at age 25.

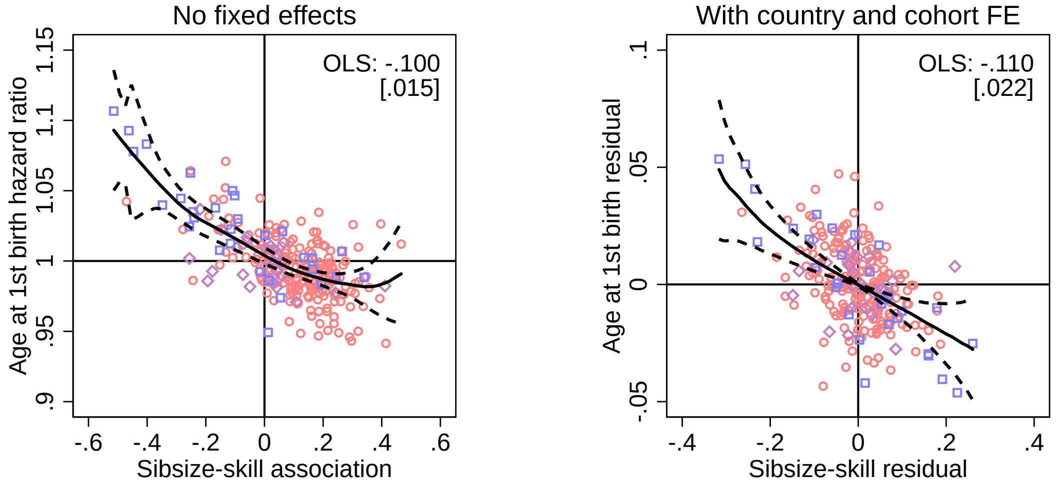
Figure 4: Intergenerational Fertility Associations vs. Sibsize-Skill Associations



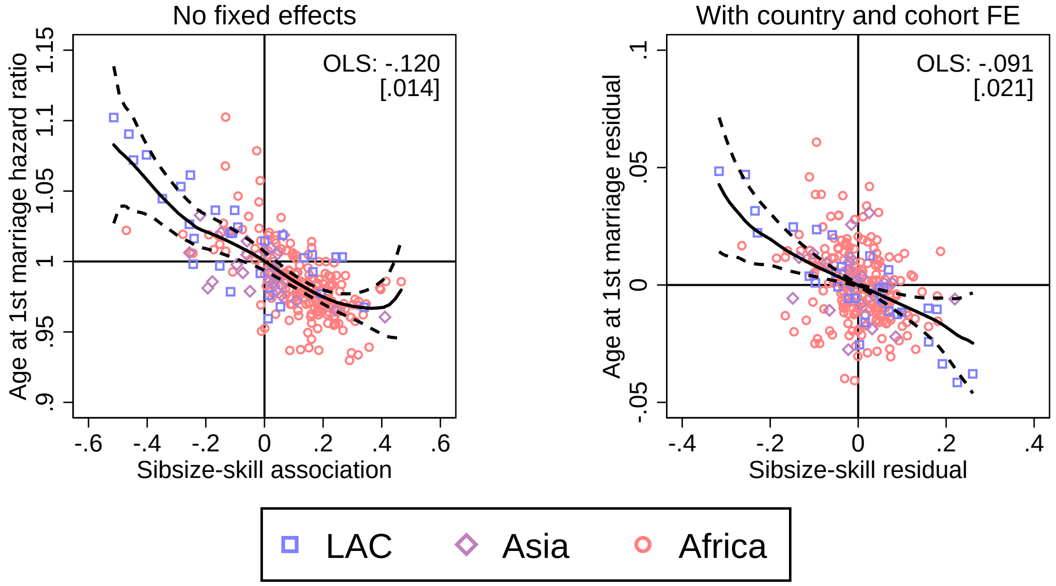
Note: Sample includes 581,143 women from 258 country-cohort cells with at least 250 observations. Solid curves are local linear regressions with bandwidths of 0.1; dashed curves are 95% confidence intervals based on bootstrapped pointwise standard errors. OLS results reported in the top right corner 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.

Figure 5: Role of Earlier Marriage and Childbearing

A. Age at first birth

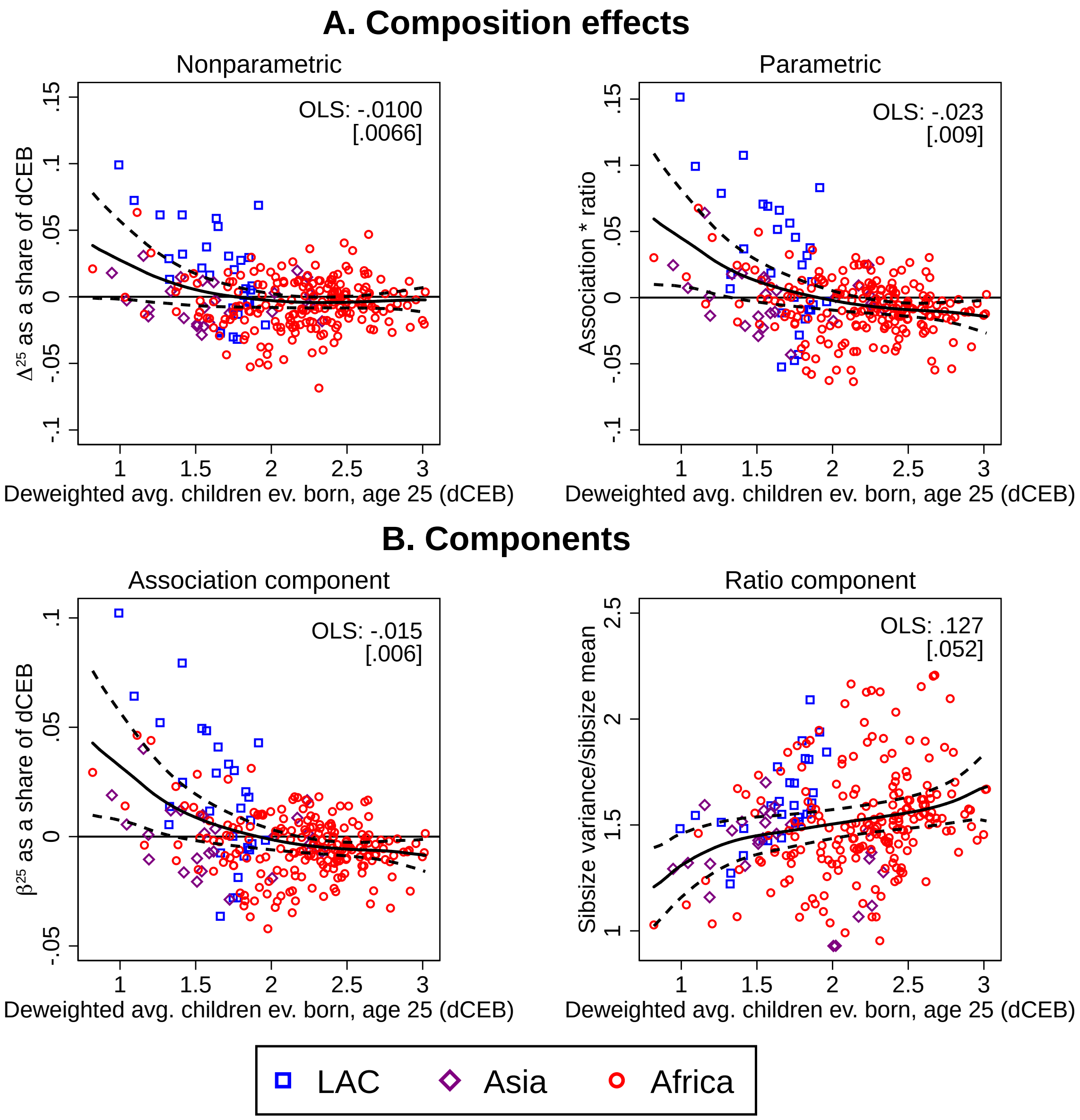


B. Age at first marriage



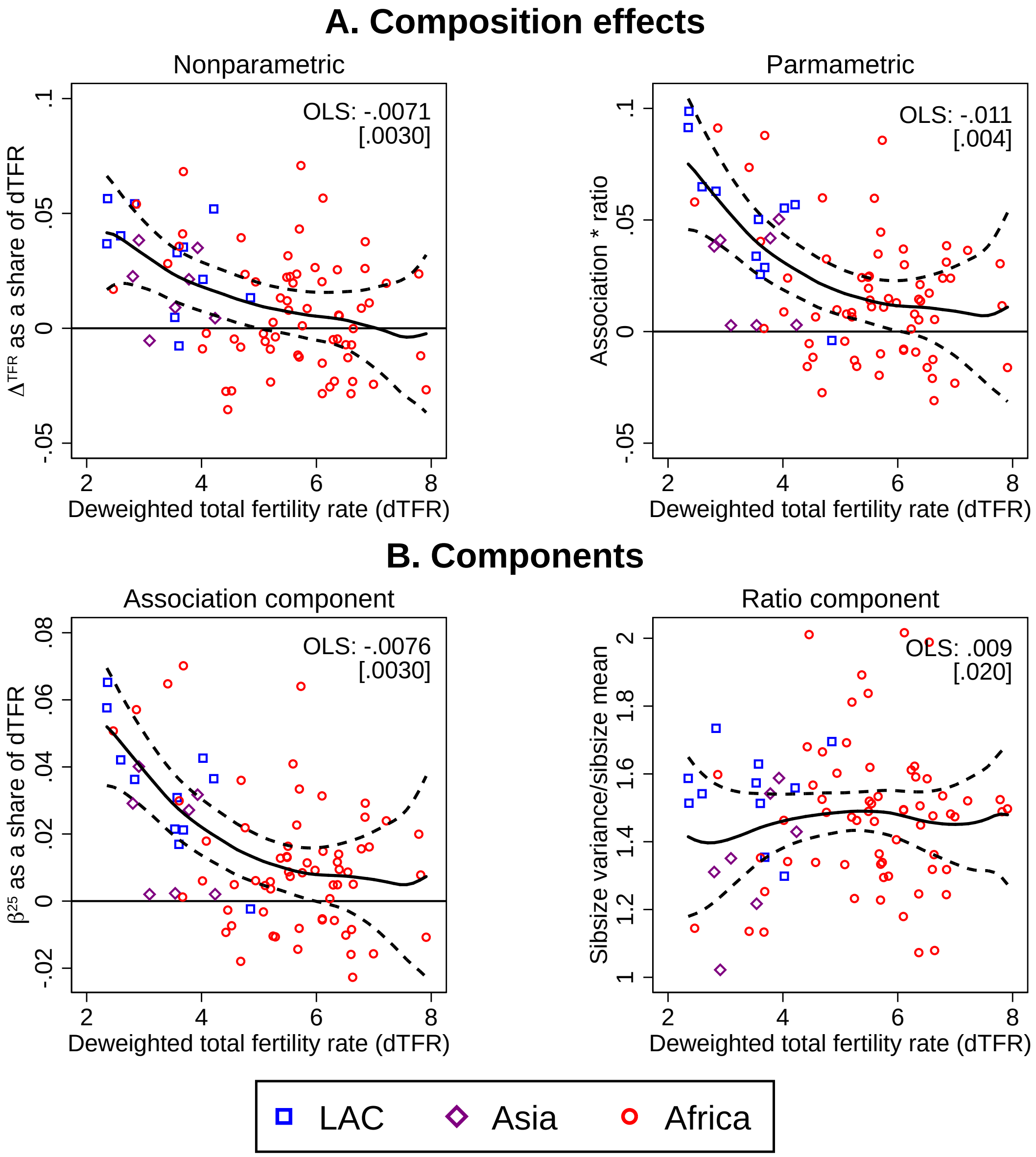
Note: Sample includes 581,143 women from 258 country-cohort cells with at least 250 observations. Solid curves are local linear regressions with bandwidths of 0.1; dashed curves are 95% confidence intervals based on bootstrapped pointwise standard errors. OLS results reported in the top right corner of each panel are slope coefficients from the analogous linear regressions, with bootstrapped standard errors in brackets. All estimations use surviving sibship size.

Figure 6: Composition Effects on Cohort Average Fertility



Note: 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.

Figure 7: Composition Effects on the Total Fertility Rate



Note: Sample includes 81 surveys. Solid curves are local linear regressions with bandwidths of 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.

Table 1: Sibship Size, Educational Attainment, and Age-25 Fertility in Bolivia

	1945-54		1955-64		1965-74		1975-83	
	Ever	Surv.	Ever	Surv.	Ever	Surv.	Ever	Surv.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Short regression (dependent variable: # children at age 25)								
# siblings (*β)*	0.0001	0.005	0.009	0.014	0.048	0.043	0.081	0.073
	[0.016]	[0.012]	[0.007]	[0.006]	[0.007]	[0.006]	[0.008]	[0.007]
B. Long regression (dependent variable: # children at age 25)								
# siblings (Β)	0.010	0.014	0.014	0.026	0.035	0.042	0.029	0.039
	[0.015]	[0.015]	[0.007]	[0.074]	[0.006]	[0.002]	[0.007]	[0.008]
Yrs. of ed. (Γ)	-0.064	-0.030	-0.082	-0.053	-0.115	-0.090	-0.130	-0.110
	[0.007]	[0.006]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
C. Auxilliary regression (dependent variable: yrs. of ed.)								
# siblings (*φ)*	0.148	0.322	0.062	0.205	-0.112	-0.010	-0.399	-0.373
	[0.048]	[0.059]	[0.024]	[0.029]	[0.022]	[0.027]	[0.029]	[0.034]
D. Means and standard deviations								
# 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)
# 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)
Yrs. of ed.	4.7 (5.4)		6.1 (5.3)		7.5 (5.1)		9.0 (5.1)	
# obs.	1,808		7,758		10,090		6,834	

Note: 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

		Distribution of *t*-statistics		
	Mean (S.D.)	$t \leq -1.96$	$-1.96 < t < 1.96$	$t \geq 1.96$
	(1)	(2)	(3)	(4)
A. Ever-born				
β (overall association)	.017 (.030)	2%	70%	29%
B (net transmission)	.014 (.020)	2%	70%	29%
Γ (skill-fertility)	-.098 (.048)	90%	29%	< 1%
φ (sibsize-skill)	.005 (.149)	26%	35%	40%
B. Surviving				
β (overall association)	.005 (.030)	9%	75%	16%
B (net transmission)	.007 (.021)	6%	77%	17%
Γ (skill-fertility)	-.070 (.050)	80%	17%	3%
φ (sibsize-skill)	.082 (.165)	16%	29%	55%

Note: 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.

Table 3: Aggregate Predictors of Intergenerational Fertility Associations

	Ever-born				Surviving			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log annual GDP per capita (PPP), Penn World Table								
At birth	0.008	0.01			0.003	0.005		
	[0.012]	[0.016]			[0.012]	[0.014]		
At age 20		-0.007				0.001		
		[0.016]				[0.018]		
Urbanization rate (0-1), UN								
At birth	0.081	0.044			-0.008	-0.064		
	[0.101]	[0.096]			[0.113]	[0.106]		
At age 20		-0.009				-0.011		
		[0.089]				[0.088]		
Infant mortality rate (0-1), UN								
At birth	0.015	0.012			-0.0003	-0.001		
	[0.015]	[0.013]			[0.011]	[0.011]		
At age 20		0.003				-0.004		
		[0.013]				[0.010]		
Average adult years of education (25+) Barro-Lee								
At birth	0.024	0.018	0.027	0.020	0.021	0.011	0.022	0.011
	[0.010]	[0.009]	[0.009]	[0.008]	[0.011]	[0.009]	[0.009]	[0.008]
At age 20		0.009		0.010		0.017		0.016
		[0.007]		[0.007]		[0.008]		[0.007]
# cells	150	150	150	150	150	150	150	150
# countries	31	31	31	31	31	31	31	31

Notes: All regressions include country and cohort fixed effects. Brackets contain standard errors clustered at the country level. Outcomes are intergenerational fertility associations based on cumulative fertility at age 25. Urbanization and infant mortality rates are scaled between 0 and 1 to reduce the number of decimal places in the coefficients.

Table 4: Composition Effects on Age-25 Fertility in Bolivia

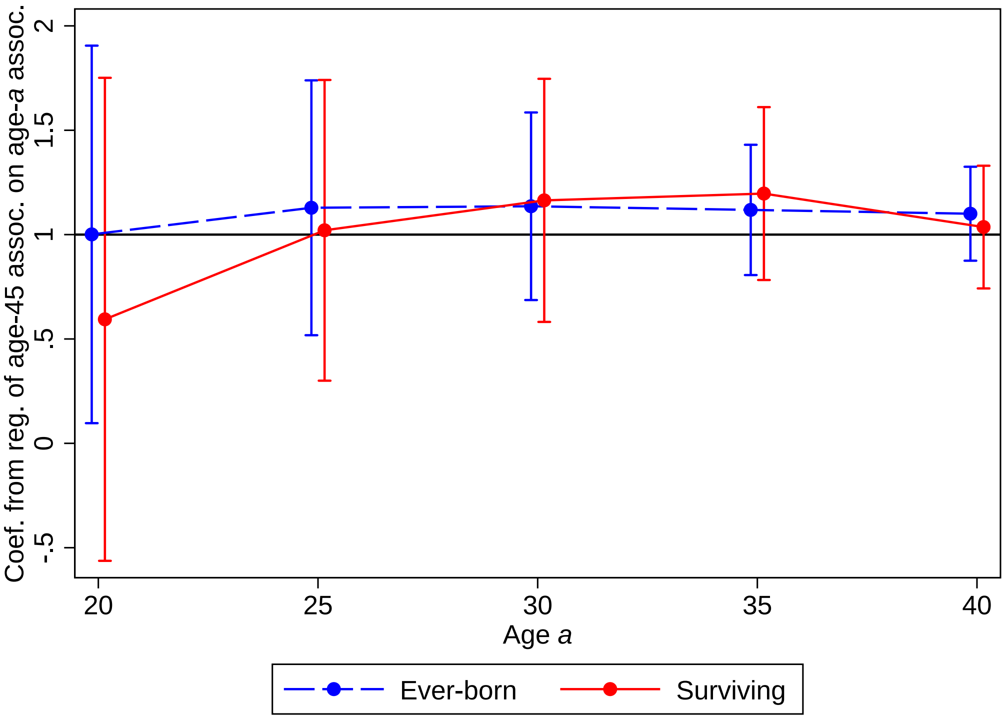
	1945-54	1955-64	1965-74	1975-83
	(1)	(2)	(3)	(4)
A. Relative Composition Effects				
Nonparametric	-0.032	-0.009	0.007	0.058
	[0.020]	[0.008]	[0.009]	[0.011]
Parametric	-0.018	0.0009	0.038	0.093
	[0.023]	[0.008]	[0.009]	[0.012]
B. Components				
Relative intergenerational association	-0.009	0.0005	0.022	0.056
	[0.011]	[0.005]	[0.005]	[0.007]
Variance/mean of sibsize	2.05	1.88	1.76	1.66
	[0.07]	[0.05]	[0.03]	[0.05]
C. Means and standard deviations				
Children ever born at age 25	1.8 (1.6)	1.9 (1.6)	1.8 (1.5)	1.6 (1.4)
Deweighted children ever born at age 25	1.9 (1.7)	1.9 (1.6)	1.8 (1.5)	1.5 (1.3)
Number of observations	1,808	7,758	10,090	6,834

Note: 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.

Appendix Table 1: Demographic and Health Surveys Included in the Sample

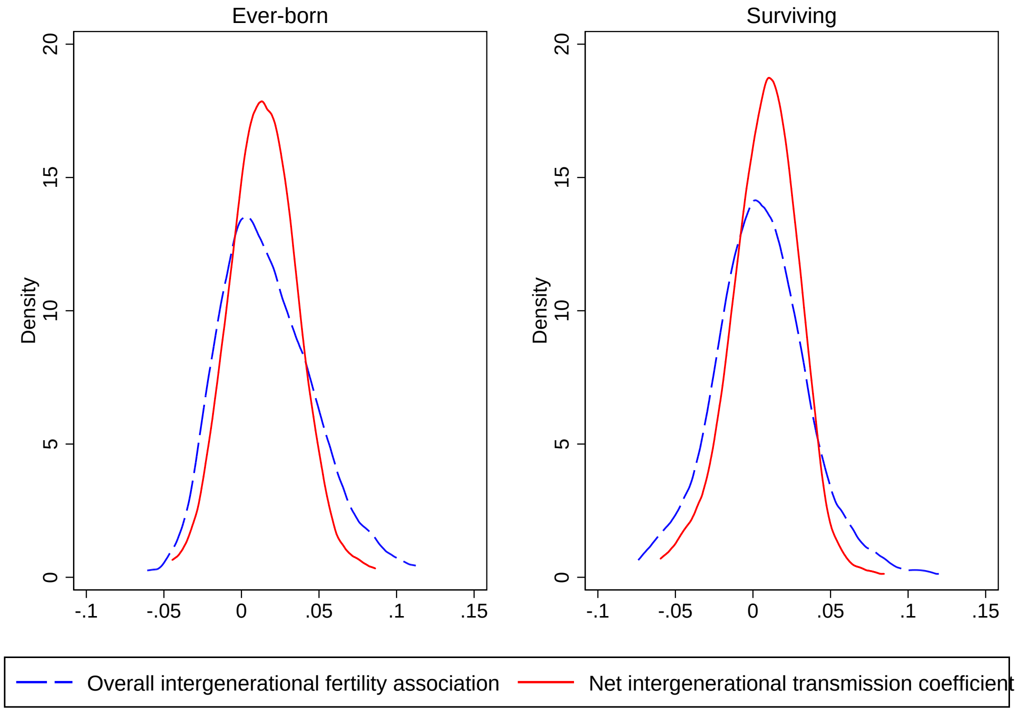
Benin: 1996, 2006
Bolivia: 1994, 2003, 2008
Burkina Faso: 1999
Burundi: 2010
Cambodia: 2000, 2005, 2010
Cameroon: 1998, 2004
Central African Republic: 1995
Chad: 1996, 2004
Congo, Democratic Republic: 2007
Congo, Republic: 2005
Cote d'Ivore: 1994
Dominican Republic: 2002, 2007
Ethiopia: 2000, 2005, 2010
Gabon: 2000
Guinea: 2000, 2005
Haiti: 2000, 2005
Indonesia: 2012
Kenya: 2003, 2008
Lesotho: 2004, 2009
Madagascar: 1992, 1997, 2004, 2008
Malawi: 1992, 2000, 2004, 2010
Mali: 1995, 2001, 2006
Morocco: 1992, 2003
Mozambique: 1997, 2003
Namibia: 1992, 2000
Nepal: 1996, 2006
Nigeria: 2008
Peru: 1992, 1996, 2000, 2004
Philippines: 1993, 1998
Rwanda: 2000, 2005, 2010
São Tomé & Príncipe: 2008
Senegal: 1992, 2005
Sierra Leone: 2008
South Africa: 1998
Sudan: 2010
Swaziland: 2007
Tanzania: 1996, 2004, 2010
Togo: 1998
Zambia: 1996, 2001, 2007
Zimbabwe: 1994, 1999

Appendix Figure 1: Choosing the Age at Fertility Measurement



Note: Sample includes 75,062 women from 95 country-cohort cells with at least 250 women over age 45. Each coefficient and 95% confidence interval comes from a separate regression of the fertility association at age 45 on the fertility association at an earlier age. Capped spikes represent 95% confidence intervals based on bootstrapped standard errors.

Appendix Figure 2: Kernel Densities of Intergenerational Fertility Associations



Note: Kernel density estimates with a bandwidth of 0.01. Sample includes 581,143 women from 258 country-cohort cells. The intergenerational fertility association is from a univariate regression, while the net intergenerational transmission coefficient is from a regression that controls for education. Fertility associations are based on cumulative fertility at age 25.