The Annals of Applied Statistics
2024, Vol. 18, No. 1, 375–403
https://doi.org/10.1214/23-AOAS1793

BAYESIAN PROJECTIONS OF TOTAL FERTILITY RATE CONDITIONAL ON THE UNITED NATIONS SUSTAINABLE DEVELOPMENT GOALS

BY DAPHNE H. LIU[1,a] AND ADRIAN E. RAFTERY[2,b]

[1]*Department of Statistics, University of Washington,* [a]*dhliu@uw.edu*
[2]*Departments of Statistics and Sociology, University of Washington,* [b]*raftery@uw.edu*

Women's educational attainment and contraceptive prevalence are two mechanisms identified as having an accelerating effect on fertility decline and that can be directly impacted by policy. Quantifying the potential accelerating effect of education and family planning policies on fertility decline in a probabilistic way is of interest to policymakers, particularly in high-fertility countries. We propose a conditional Bayesian hierarchical model for projecting fertility, given education and family planning policy interventions. To illustrate the effect policy changes could have on future fertility, we create probabilistic projections of fertility that condition on scenarios such as achieving the sustainable development goals (SDGs) for universal secondary education and universal access to family planning by 2030.

1. Introduction. World population in the next century will be driven by high-fertility countries. The United Nations projects that more than half of the projected increase in world population from 7.8 billion people in 2020 to 10.9 billion people in 2100 will occur in high-fertility countries, primarily in sub-Saharan Africa (United Nations (2019a)). Much of the rest of the population increase is projected to occur in countries with above-replacement fertility, mostly in Asia and Latin America.

Policymakers in these countries have an interest in slowing this population increase by accelerating fertility decline, as high fertility and rapid population growth may have adverse economic, environmental, health, governmental, and political consequences (Bongaarts (2013)). Reductions in fertility can also benefit the economy through what is known as the demographic dividend, where declining fertility can lead to accelerated economic growth by reducing the dependency ratio, increasing women's participation in the paid labor force, and allowing increased investments in human and physical capital (Lee and Mason (2006), Mason and Lee (2006)).

There is widespread agreement in the demographic literature that increasing education and increasing family planning are the two main factors that can be influenced by policy and may help accelerate fertility decline (Hirschman (1994)). Education is thought to accelerate fertility decline by increasing the opportunity cost of having children for women and by increasing the cost of raising children (Caldwell (1982), Caldwell, Reddy and Caldwell (1985), Easterlin and Crimmins (1985), Axinn and Barber (2001)). These increased costs are evident in education differentials in fertility that have been observed across countries, with more highly educated women tending to have fewer children than less educated women (Martín (1995), Bongaarts (2003)).

Family planning is also thought to accelerate fertility decline, as family planning is needed to translate changes in fertility desires into changes in realized fertility. Contraceptive prevalence, in particular, is a proximate determinant of fertility that provides a venue for individuals to achieve their desired childbearing (Bongaarts (1987)). Liu and Raftery (2020) found

Received April 2022; revised March 2023.
Key words and phrases. Bayesian hierarchical model, fertility, sustainable development goals.

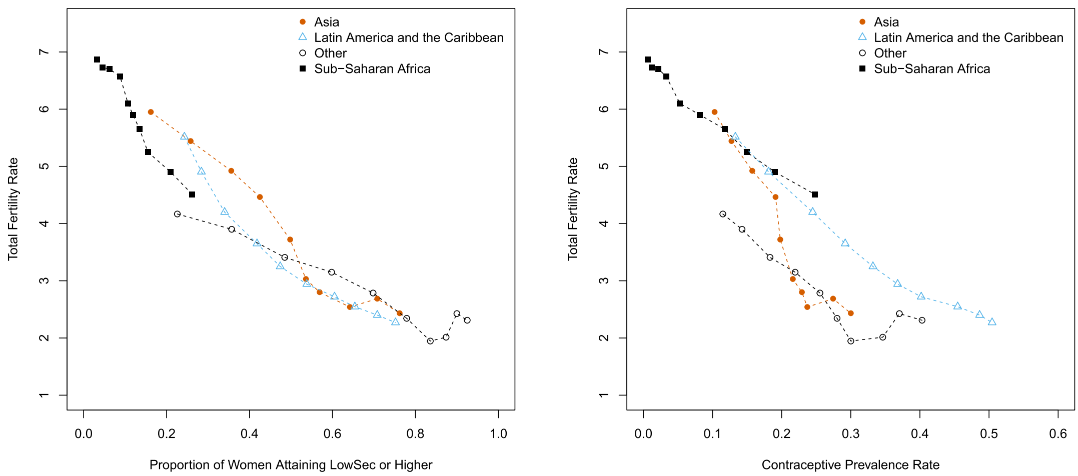

FIG. 1. *Relationship between the median total fertility rate, the median proportion of women attaining lower secondary (LowSec) education or higher, and the median contraceptive prevalence rate of modern methods plotted as time series covering five-year time periods from* 1970–1975 *to* 2015–2020 *for each region. Only countries used to estimate the second stage of the conditional TFR projection model and only time periods corresponding to when the country was in Phase II of the fertility transition were used to calculate the medians.*

significant accelerating effects of women's educational attainment and contraceptive prevalence on fertility decline in the high-fertility setting. That is, we found that faster increases in women's educational attainment and contraceptive prevalence, for example, due to policy interventions, were associated with faster increases in the pace of fertility decline beyond what we would expect the fertility decline to look like assuming no policy intervention. We found that the accelerating effect of education on fertility operates through increasing mother's education rather than through increasing children's enrollment and that the attainment level with the largest effect size was lower secondary education or higher. The accelerating effect of family planning on fertility was found to operate primarily through increasing contraceptive prevalence of modern contraceptive methods rather than through decreasing unmet need for family planning.

Figure 1 shows the relationship between the median total fertility rate, the median proportion of women attaining lower secondary education or higher, and the median contraceptive prevalence rate of modern methods for different world regions, plotted as time series covering the five-year time periods 1970–1975 to 2015–2020. We can see a strong negative association between educational attainment and fertility and between contraceptive prevalence and fertility across regions.

There is also evidence to suggest that interventions related to education and family planning may have a smaller accelerating effect on fertility in sub-Saharan Africa (SSA) than elsewhere. Most of the world's currently high-fertility countries are located in SSA, and the fertility transition being experienced in SSA is slower than the historical fertility transitions observed in Asia and Latin America (Bongaarts and Casterline (2013)), where the fertility transition refers to the decline from high to low fertility that occurs as a country develops. The relationships between education, family planning, and fertility are different in SSA than in other regions, with higher fertility and lower contraceptive use for a given level of education compared to other regions (Bongaarts, Mensch and Blanc (2017)). Differences in ideal family size may diminish the effect of family planning policy interventions in SSA (Bongaarts, Frank and Lesthaeghe (1984), Bongaarts and Casterline (2013)), while differences in school quality may diminish the effect of education policy interventions (Grant (2015)). Liu and Raftery (2020) found that the accelerating effect that increases in women's educational attainment and increases in contraceptive prevalence have on fertility decline were indeed smaller in SSA compared to other regions.

This raises the question of how the accelerating effects of women's educational attainment and contraceptive prevalence could impact future fertility and population size in high-fertility countries, particularly in the context of meeting policy goals for education and family planning. Two of the United Nations Sustainable Development Goals (SDGs) refer directly to increasing educational attainment and increasing access to family planning and thus are likely to have an effect on future population.

The SDGs are a set of goals related to global development that were identified by the United Nations as a follow-up to the previous Millennium Development Goals. The SDGs were established in 2015 with a target date of completion in 2030. The SDG targets that relate directly to education and family planning are Targets 4.1 and 3.7. Target 4.1 relates to universal educational attainment goals, specifically, "By 2030, ensure that all girls and boys complete free, equitable and quality primary and secondary education leading to relevant and effective learning outcomes." Target 3.7 includes goals related to family planning, specifically, "By 2030, ensure universal access to sexual and reproductive health-care services, including for family planning, information and education, and the integration of reproductive health into national strategies and programmes" (United Nations (2015)).

The United Nations (U.N.) has produced estimates and projections of world population by country since 1951 and remains the premier producer of global demographic projections, with projections from the U.N. used by policymakers around the world. In particular, governments and agencies in countries that do not have robust vital registration systems of their own often rely on the U.N. estimates and projections to inform planning and policy decisions. However, the U.N. does not currently produce projections for policy-based scenarios, although projection variants (low, medium, and high) based on different underlying demographic assumptions are available. The low and high projection variants for fertility correspond to assuming the total fertility rate (TFR) will be, respectively, half a child below or half a child above the medium variant TFR. While these variants can provide some guidance to policymakers, they have the drawback of being deterministic with no statistical interpretation.

Two other producers of global demographic projections, the Wittgenstein Centre for Demography and Global Human Capital and the Institute for Health Metrics and Evaluation (IHME), do produce scenario-based projections of fertility and population that include scenarios corresponding to attaining the SDGs in 2030 (Abel et al. (2016), Vollset et al. (2020)). These existing population projections based on policy scenarios either do not fully incorporate uncertainty or do not fully incorporate field-specific demographic knowledge. There are also substantial differences between the reference scenario projections produced by the U.N. and the reference scenario projections produced by both the Wittgenstein Centre and IHME due to differences in methodology and underlying assumptions, so the policy-based projections from other sources cannot be directly compared with the U.N. reference scenario projections. Demographic projections based on policy scenarios using the U.N. methodology are thus of interest.

The U.N. projection model for TFR currently does not explicitly incorporate the effect of covariates, whereas the Wittgenstein Centre emphasizes the effect of education on fertility and IHME incorporates the effects of both education and family planning in their fertility model. Instead, the U.N. projection model implicitly captures the effect of covariates on fertility by modeling future TFR based on historical trends in TFR. However, for policymaking it may be important to incorporate these covariates explicitly into fertility projection models (Lutz, Butz and KC (2014)).

Here we develop a conditional probabilistic projection model for TFR that extends the probabilistic fertility projection model used by the U.N.. The conditional TFR projection model explicitly accounts for women's educational attainment, contraceptive prevalence of modern methods, and GDP per capita and allows for the creation of projections of TFR that are conditional on policy-based intervention scenarios related to education and family planning. Using a Bayesian framework, we address the question of what the quantitative effect of meeting SDG Targets 3.7 and 4.1 would be on future fertility and population.

This paper is organized as follows. In Section 2 we describe the data and methods. Section 3 presents the projection results for TFR and population size, using Nigeria as a case study. We also present regional aggregate results for sub-Saharan Africa. In Section 4 we describe the out-of-sample validation results for the conditional TFR projection model. In Section 5 we discuss and compare our results with related work. Finally, we summarize the findings of this paper in Section 6.

2. Methods.

2.1. *Data*. Estimates of TFR were obtained from the United Nations *World Population Prospects* (WPP) 2019 Revision (United Nations (2019a)). TFR is a period measure of fertility that measures the expected number of children a woman would bear in her lifetime if she were to experience the period-specific fertility rates at each age and if she lived through the reproductive age range, here defined as ages 15–49. The estimates from WPP 2019 are available for 201 countries by five-year time periods, are comparable across countries and time periods, and are based on vital registers, censuses, and surveys such as the Demographic and Health Surveys (DHS) and the Multi-Indicator Cluster Surveys (MICS).

Estimates of educational attainment for women in the broad age group 20–39 were obtained from the Wittgenstein Centre Data Explorer Version 2.0 (Wittgenstein Centre (2018), Lutz et al. (2018)). The Wittgenstein Centre produces a harmonized data set of the educational attainment distribution that is comparable across countries and times. The educational attainment distribution uses six levels of attainment based on the International Standard Classification of Education: no education, incomplete primary, primary, lower secondary, upper secondary, and postsecondary. We focus on cumulative attainment, specifically, on the proportion of women attaining lower secondary education or higher, abbreviated as LowSec+. Liu and Raftery (2020) found this to be the summary measure of education most closely associated with fertility decline.

Probabilistic projections of educational attainment were created following the Wittgenstein Centre methodology using the "wicedproj" package[1] in R, which was released alongside Abel et al. (2016). Figure 2 illustrates estimates and projections of women's attainment of LowSec+ for Nigeria. Intervention-based probabilistic projections of educational attainment corresponding to achieving the SDGs were obtained using the methodology developed by Abel et al. (2016) with further details in Section 2 of the Supplementary Material (Liu and Raftery (2024)).

Estimates and projections of contraceptive prevalence of modern methods for all women aged 15–49 were obtained following the methodology of Kantorová et al. (2020). Kantorová et al. created probabilistic estimates and projections of family planning indicators using a Bayesian hierarchical model, which is implemented in the "FPEMglobal" package[2] in R. We used the median estimates of contraceptive prevalence of modern methods from a converged simulation of FPEMglobal as an input to our TFR projection model, where contraceptive prevalence is a proportion between 0 and 1 and is constructed for five-year time periods from 1970–1975 through 2015–2020. Probabilistic projections of contraceptive prevalence from

[1] Available at https://github.com/bifouba/wicedproj, downloaded on June 17, 2020.
[2] Available at https://github.com/FPcounts/FPEMglobal, version 1.1.0 downloaded on June 17, 2020.

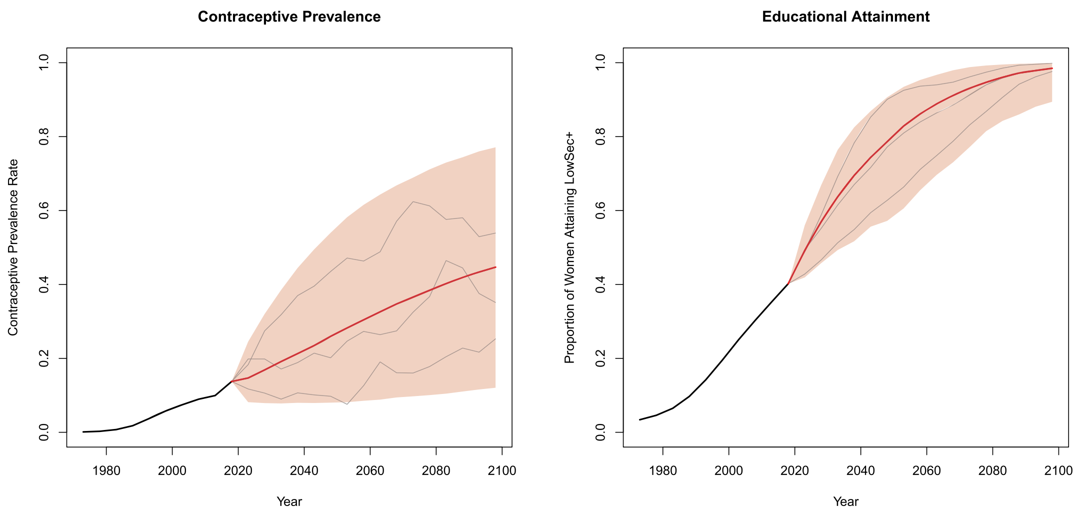

FIG. 2. *Estimates and nonintervention projections of contraceptive prevalence of modern methods for all women and proportion of women attaining lower secondary education or higher for Nigeria from* 1970–1975 *to* 2095–2100. *Estimates of the past are plotted in black, medians and* 95% *intervals for projections are plotted in red, and sample projection trajectories are plotted in grey.*

2020–2025 to 2095–2100 were similarly obtained using a converged simulation of FPEM-global. Figure 2 illustrates estimates and projections of contraceptive prevalence for Nigeria. Intervention-based probabilistic projections of contraceptive prevalence corresponding to meeting the SDGs were created by modifying the nonintervention projections. Details of the SDG intervention projections of contraceptive prevalence can be found in Section 2.5 with further details in Section 2 of the Supplementary Material (Liu and Raftery (2024)).

Estimates of GDP per capita were obtained from the Maddison Project (Maddison Project (2018)), and projections of GDP were obtained using a Bayesian hierarchical model developed by Raftery et al. (2017). As we are not interested in interventions targeting GDP, we considered only nonintervention projections of GDP for our conditional TFR projections.

2.2. *Model.* We build upon the unconditional model for probabilistic fertility projections that is the basis for fertility projections produced by the U.N. (Alkema et al. (2011), Raftery, Alkema and Gerland (2014), Fosdick and Raftery (2014)). The unconditional model is a Bayesian hierarchical model that has been implemented in the R package "bayesTFR" (Ševčíková, Alkema and Raftery (2011)).[3] The unconditional fertility projection model, referred to in this paper as the "bayesTFR" model, divides the fertility transition into three phases, as defined by Alkema et al. (2011): Phase I is the high-fertility pretransition phase, Phase II is the transition phase where fertility falls from high to low, and Phase III is the low-fertility posttransition phase. Since all or almost all countries have already begun the fertility transition, Phase I is not needed for TFR projections and thus is not modeled. The bayesTFR Phase II and Phase III models as well as our modifications to the Phase II model are described in this section.

In the bayesTFR Phase II model, fertility decline is modeled as a random walk with drift, where the drift term represents the systematic decline. Let $f_{c,t}$ denote the TFR in country c and five-year time period t. Decrements in TFR are constructed as a measure of fertility decline, with the TFR decrement between five-year time periods t and $(t + 1)$ defined as

[3]bayesTFR version 6.4.0 was used for this paper.

$\Delta f_{c,t+1} = f_{c,t+1} - f_{c,t}$. The unconditional Phase II model is written

$$\begin{aligned}\Delta f_{c,t+1} &= f_{c,t+1} - f_{c,t} \\ &= -g(f_{c,t}|\boldsymbol{\theta}_c) + \varepsilon_{c,t}, \\ \boldsymbol{\theta}_c &\sim h(\cdot|\phi), \\ \phi &\sim \pi(\cdot),\end{aligned}$$

where $g(f_{c,t}|\boldsymbol{\theta}_c)$ is a five-parameter double logistic function that represents the expected TFR decrement from five-year time period t to five-year time period $(t+1)$. The double logistic function is defined as

$$\begin{aligned}g(f_{c,t}|\boldsymbol{\theta}_c) = {} & \frac{-d_c}{1 + \exp(-2\frac{\ln(9)}{\Delta_{c1}}(f_{c,t} - \sum_i \Delta_{ci} + 0.5\Delta_{c1}))} \\ & + \frac{d_c}{1 + \exp(-2\frac{\ln(9)}{\Delta_{c3}}(f_{c,t} - \Delta_{c4} - 0.5\Delta_{c3}))}\end{aligned}$$

and takes the current value of TFR $(f_{c,t})$ and a vector of country-specific parameters $\boldsymbol{\theta}_c = (\Delta_{c1}, \Delta_{c2}, \Delta_{c3}, \Delta_{c4}, d_c)$ as inputs. The country-specific parameter vector specifies the shape of each country's individual decline curve and follows a world distribution $h(\cdot|\phi)$ with parameter ϕ, where the prior distribution of ϕ is $\pi(\cdot)$. Further details of the decline function can be found in Section 1 of the Supplementary Material (Liu and Raftery (2024)).

The error term for each five-year time period t in the bayesTFR Phase II model is given by

$$\varepsilon_{c,t} \sim \begin{cases} N(m_t, s_t^2) & \text{for } t = \tau_c \\ N(0, \sigma(f_{c,t})^2) & \text{otherwise,} \end{cases}$$

where τ_c is the start time period of Phase II, m_τ is the mean of the error in the start period, and s_τ is the standard deviation of the error in the start period. In time periods following the start of the fertility transition, the standard deviation depends on the current level of the TFR and is given by the function $\sigma(f_{c,t})$, with details given in Section 1 of the Supplementary Material (Liu and Raftery (2024)).

Accounting for between-country correlation in TFR is important when constructing aggregates, such as regional or world TFR. The bayesTFR projection model accounts for between-country correlation in projections using a pairwise likelihood method developed by Fosdick and Raftery (2014), which models correlation between countries i and j as a function of whether countries i and j are contiguous, whether they had a common colonizer after 1945, and whether they belong to the same U.N. region. In estimation of the bayesTFR model, the error terms are assumed to be independent.

We create a conditional TFR projection model by extending the unconditional Phase II model to include a covariate term and to account for between-country correlation in estimation. Covariates were constructed as changes over time on the same scale as the TFR decrements $\Delta f_{c,t+1}$. For example, the change over time from t to $(t+1)$ for covariate X is denoted by $\Delta X_{c,t+1}$. The covariates added are the change over time in the proportion of women aged 20–39 who have attained at least lower secondary education, denoted by ΔLowSec+, the change over time in the contraceptive prevalence of modern methods for all women of reproductive age, denoted by ΔCP, and the percent change in GDP per capita, denoted by ΔGDP. Each covariate is centered at its expected value assuming no policy intervention, with details of the centering found in Section 1 of the Supplementary Material (Liu and Raftery (2024)). The centering ensures the covariates reflect acceleration in the trends for women's educational attainment, contraceptive prevalence, or GDP per capita beyond what we would expect these trends to look like, assuming no policy intervention. For example, if women's educational attainment increases at the pace expected under no policy intervention, the covariate ΔLowSec+ will be close to 0. However, if women's educational attainment increases at a faster pace than expected under no policy intervention, the covariate ΔLowSec+ will be greater than 0. We also consider interaction terms between the covariates and an indicator function SSA_c for whether country c is in sub-Saharan Africa.

The conditional TFR projection model is specified as

$$\begin{aligned}
\Delta f_{c,t+1} &= f_{c,t+1} - f_{c,t} \\
&= -g(f_{c,t}|\boldsymbol{\theta}_c) + \boldsymbol{\Delta}\mathbf{X}_{c,t}\boldsymbol{\beta} + \varepsilon_{c,t},
\end{aligned}$$

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_E \\ \beta_F \\ \beta_G \\ \beta_{E,\mathrm{SSA}} \\ \beta_{F,\mathrm{SSA}} \\ \beta_{G,\mathrm{SSA}} \end{bmatrix}, \qquad \boldsymbol{\Delta}\mathbf{X}_{c,t}^T = \begin{bmatrix} (\Delta\mathrm{LowSec+})_{c,t} \\ (\Delta\mathrm{CP})_{c,t} \\ (\Delta\mathrm{GDP})_{c,t} \\ (\Delta\mathrm{LowSec+})_{c,t} \times \mathrm{SSA}_c \\ (\Delta\mathrm{CP})_{c,t} \times \mathrm{SSA}_c \\ (\Delta\mathrm{GDP})_{c,t} \times \mathrm{SSA}_c \end{bmatrix},$$

$$\beta_j \sim N\left(0, 0.25 \times \frac{\mathrm{Var}(\Delta f)}{\mathrm{Var}(\Delta X_j)}\right) \quad \text{for } j \in (E; F, G; E, \mathrm{SSA}; F, \mathrm{SSA}; G, \mathrm{SSA}).$$

The prior distributions of the coefficients β_j were chosen to be diffuse, where the prior variances are determined by the ratio of the sample variance of observed changes in f to the sample variance of observed changes in X_j.

We account for between-country correlation in the estimation of the conditional model using clusters based on U.N. region membership. Each U.N. region consists of countries that are both spatially contiguous and relatively culturally homogeneous, so we expect similar between-country correlation for all countries in the same U.N. region and at the same time period. Let $\tilde{\boldsymbol{\sigma}}$ denote the vector of values of $\sigma(f_{c,t})$ ordered by U.N. Region and time period. The error term for the conditional TFR projection model is specified as

$$\begin{aligned}
\boldsymbol{\varepsilon} &\sim N(0, \Sigma), \\
\Sigma &= \mathrm{diag}(\tilde{\boldsymbol{\sigma}}) \cdot R \cdot \mathrm{diag}(\tilde{\boldsymbol{\sigma}}), \\
R[i,j] &= \begin{cases} 1 & \text{if } i = j, \\ \rho^{[bc]} & \text{if } i, j \in \text{ same U.N. region and same time period }, \\ 0 & \text{otherwise,} \end{cases} \\
\rho^{[bc]} &\sim \mathrm{Uniform}(0, 1),
\end{aligned}$$

where the (i, j)th term of the correlation matrix R represents the correlation between country-time pair i and country-time pair j. If observations i and j are from the same time period and refer to countries within the same U.N. region, the between-country correlation is $\rho^{[bc]}$. Further details of the conditional TFR projection model can be found in Section 1 of the Supplementary Material (Liu and Raftery (2024)).

To create fertility projections, we use the same unconditional posttransition Phase III model as bayesTFR. The posttransition phase represents what happens to a country's TFR once it has completed the fertility transition in Phase II, where the end of Phase II is defined by the U.N. as the midpoint of the five-year time periods where two successive increases in TFR have been observed after TFR has fallen below two children per woman (United Nations (2019b)). In Phase III fertility is assumed to converge toward and fluctuate around country-specific long-term TFR levels. It is modeled as a first-order autoregressive (or AR(1)) time series model written as

$$f_{c,t+1} \sim N\big(\mu_c + \rho_c(f_{c,t} - \mu_c), s^2\big),$$

where μ_c is the long-term mean for country c. The country-specific means μ_c are assumed to be drawn from a world distribution with mean μ, which itself has a prior distribution restricting it to be no greater than replacement-level fertility, that is, $\mu \leq 2.1$. The country-specific autoregressive parameter ρ_c is restricted to $0 < \rho_c < 1$, and s is the standard devation of the random errors. The Phase III model is estimated using a Bayesian hierarchical model with further details available in Alkema et al. (2011) and Raftery, Alkema and Gerland (2014).

2.3. *Causal assumptions*. The primary goal of creating the conditional TFR projection model is to create intervention-based projections of TFR for interventions corresponding to policy outcomes, which is an inherently causal goal. The directed acyclic graph (DAG) in Figure 3 illustrates the causal assumptions underlying our analysis that are necessary for the causal interpretation of intervention-based projections of TFR from the conditional projection model.

Each node in the DAG represents a time-varying variable, where single-bordered nodes represent continuous variables and double-bordered nodes represent nodes that are deterministic functions of their parents. TFR decline from time t to time $(t+1)$ is represented by the node labeled Δf_{t+1}. TFR at time t is represented by the node labeled f_t. Given its parents

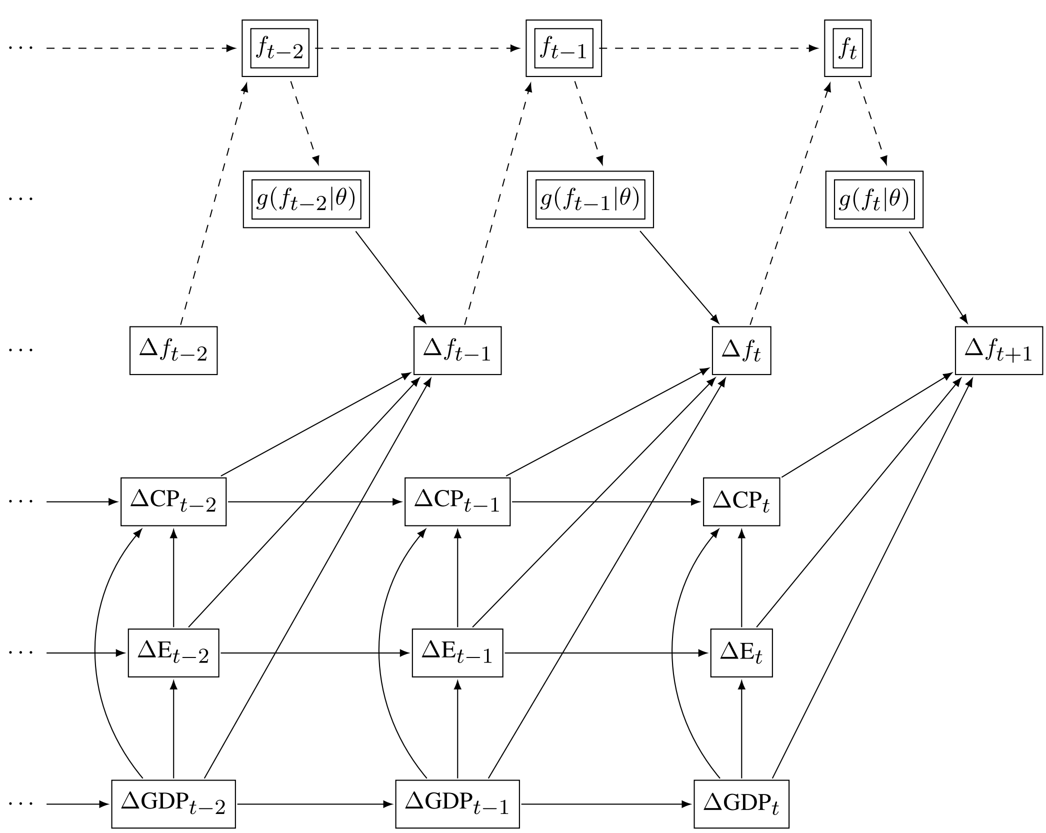

FIG. 3. *Directed acyclic graph* (*DAG*) *for TFR* f, *the double logistic expected TFR decrement term* g, *contraceptive prevalence CP, educational attainment E, and GDP per capita GDP. Single-bordered rectangles denote nodes representing continuous variables*, *and double-bordered rectangles denote nodes that are deterministic functions of their parents. Deterministic relationships are indicated by dashed arrows while stochastic relationships are indicated by solid arrows.*

f_{t-1} and Δf_t, f_t can be calculated deterministically and thus is represented as a double-bordered node. The expected TFR decrement from time t to time $(t+1)$ is represented by the node labeled $g(f_t|\boldsymbol{\theta})$. Given the parameters of the double logistic curve $\boldsymbol{\theta}$, $g(f_t|\boldsymbol{\theta})$ is a deterministic function of its parent f_t and thus is represented as a double-bordered node.

The covariate nodes are labeled as ΔCP for the contraceptive prevalence term, ΔE for the educational attainment term, and ΔGDP for the GDP per capita term. Each covariate node represents the main effect of the covariate and its interaction with the SSA indicator. For example, the $\Delta \mathrm{E}_t$ node represents the contribution of both $(\Delta\mathrm{LowSec}+)_t$ and $(\Delta\mathrm{LowSec}+)_t \times \mathrm{SSA}$.

Each dashed arrow in the DAG represents a deterministic relationship, while each solid arrow represents an assumed causal relationship in the direction indicated by the arrow. These causal relationships are informed by demographic background knowledge, primarily the proximate determinants framework for fertility developed by John Bongaarts (Bongaarts (1978), Bongaarts, Frank and Lesthaeghe (1984), Bongaarts (2010)).

Child mortality and urbanization, two key variables associated with the fertility transition, are assumed to be mediated through variables included in the DAG. Liu and Raftery (2020) found that the effect of child mortality on fertility decline was mediated through the double logistic expected TFR decrement. We found an insignificant effect of child mortality decrement on TFR decrement after controlling for the double logistic expected TFR decrement term. We also found that inclusion of the child mortality decrement did not improve model fit.

Urbanization is assumed to be mediated through the GDP term. Liu and Raftery (2020) found this to be the case, where the effect of urbanization was insignificant after controlling for GDP. There is considerable debate about causal relationships underlying modernization variables, such as GDP and urbanization, and fertility decline (Hirschman (1994), de Silva and Tenreyro (2017)). The potential for reverse causality between GDP and fertility decline, where past values of fertility decline cause future values of GDP, is omitted from our DAG, though studies such as Herzer, Strulik and Vollmer (2012) suggest this causal pathway may exist. We note that the inclusion of reverse causal paths like $\Delta f_{t-1} \rightarrow \Delta\mathrm{GDP}_t$ in the DAG does not change the assumptions needed for a causal interpretation of interventions on education and family planning.

We follow the logic of the back-door criterion, introduced by Pearl (1993), to identify the adjustment set W needed to estimate the causal effect that interventions on $X = \{\Delta\mathrm{E}_t, \Delta\mathrm{CP}_t\}$ have on $Y = \{\Delta f_{c,t+1}\}$. We find that the set $W = \{g(f_t|\boldsymbol{\theta}), \Delta\mathrm{GDP}_t\}$ satisfies the generalized back-door criterion developed by Maathuis and Colombo (2015). The set W does not contain descendants of X, and for every X_i in X, the set $W \cup X\backslash\{X_i\}$ blocks every back-door path from X_i to Y. Following Theorem 3.1 from Maathuis and Colombo (2015), W is then an appropriate adjustment set for estimating the causal effect of X on Y. In the conditional projection model, we include all elements of the adjustment set as covariates. Thus, under the assumptions underlying the DAG in Figure 3, our estimated effects can be interpreted as causal.

2.4. *Estimation.* The conditional projection model is estimated using a Markov chain Monte Carlo algorithm with Gibbs sampling, Metropolis–Hastings, and slice sampling steps. We estimated the conditional TFR projection model in two stages. In the first stage, the country-specific parameters $\boldsymbol{\theta}_c$ for the double logistic expected TFR decrement function were estimated in the absence of the covariates. In the second stage, the $\boldsymbol{\beta}$ coefficients were estimated jointly, conditionally on the posterior distributions of the double logistic parameters from the first stage. Using two stages for estimation allows us to preserve the demographic interpretation of the double logistic parameters, while still explicitly accounting for the effect of covariates in the TFR projection model.

The first stage was estimated analogously to the U.N. projection model, using estimates of TFR for 201 countries spanning 1950–1955 through 2015–2020 from WPP 2019. This allowed us to use all the available data to estimate the double logistic expected TFR decrement term and ensured that our estimates of $\boldsymbol{\theta}_c$ were comparable to the estimates used by the U.N..

In the second stage, we were primarily interested in the accelerating effect of education and family planning policy interventions on future TFR in the high-fertility setting. We thus restricted the subset of data used for estimation of the second stage to consider only current and historical “high-fertility” transitions, defined for each country as the time periods where the country had begun the fertility transition and had TFR greater than 2.5. Countries without available covariate data were excluded from analyses in the second stage. This resulted in a subset of 114 countries with 1007 observations, where the earliest time period for which we have data is 1970–1975. The top panel of Figure 4 shows the number of observations from each country included in the second stage of estimation.

Estimating the effect of education and family planning on TFR in a second stage conditional on the double logistic parameters also provides us with an interpretation of the coefficients that better lends itself to the intervention setting. For example, the covariate ΔLowSec+ measures the rate of increase in women's educational attainment beyond what would be expected if no policy intervention targeting education occurred. An accelerating effect of education on fertility decline occurs if larger values of ΔLowSec+ correspond to faster declines in TFR than what we would expect TFR decline to be, assuming no intervention targeting education. By estimating the effect of the covariates in a second stage, β_E estimates precisely this effect. The coefficient β_E can then be interpreted as the effect ΔLowSec+ has on TFR decline after we account for the pace of the fertility decline as estimated by the double logistic function, controlling for the other covariates.

2.5. *Projection.* Our focus is on creating intervention-based projections of TFR in the high-fertility setting. The relationships between education, family planning, and fertility decline, estimated in the high-fertility context, may not apply once fertility has declined to around replacement level. For example, there is evidence that the effect of educational attainment on fertility decline may be weaker in the low-fertility setting than in the high-fertility setting (Asderá (2017a), Sobotka, Beaujouan and Bavel (2017)). Due to these differing relationships, we created intervention-based projections only for countries with TFR ≥ 2.1 in 2015–2020 that have available covariate data, which are highlighted in blue in the bottom panel of Figure 4. TFR projections for countries with current TFR less than 2.1 and countries without available covariate data were created using the bayesTFR Phase II model. Note that for our purposes, TFR projections for low-fertility countries and countries without available covariate data were primarily of interest to produce projections for the sub-Saharan Africa regional aggregate. Within sub-Saharan Africa, there is one country with current TFR < 2.1 and eight countries without available covariate data. For all countries the posttransition phase was projected using the bayesTFR Phase III model.

As an input to the conditional TFR projections, we require probabilistic projections for each of the covariates. Uncertainty about the future values of the covariates is propagated into the conditional projections of TFR by randomly drawing from the projected distributions of the covariates when constructing each trajectory of projected TFR. That is, for each projected trajectory of TFR for country c, we use one trajectory from the projected distribution of ΔLowSec+ for country c, one trajectory from the projected distribution of ΔCP for country c, and one trajectory from the projected distribution of ΔGDP for country c. The resulting distribution of conditional TFR projections reflects both the uncertainty from the conditional TFR projection model parameters and uncertainty from the covariate projections.

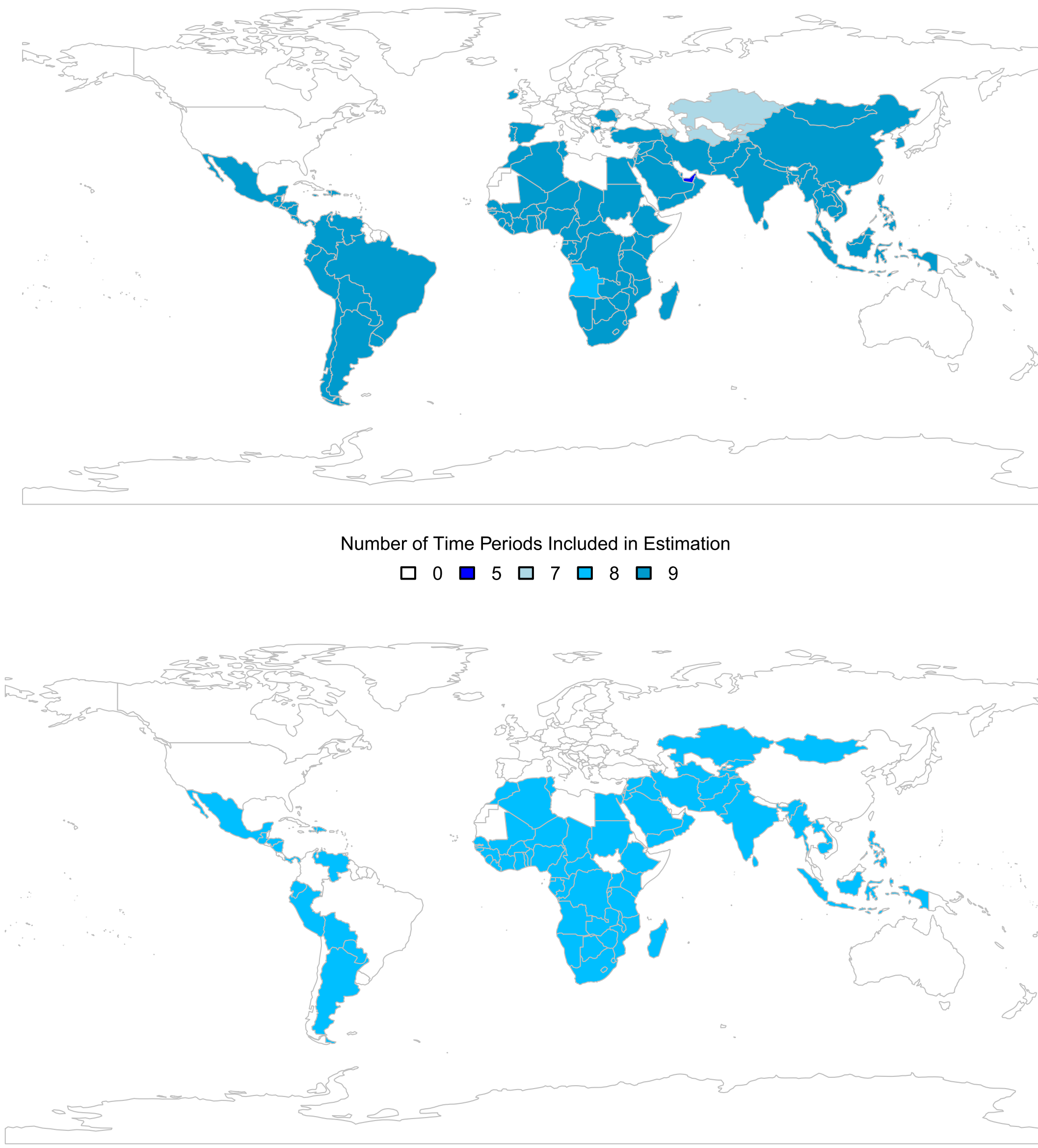

FIG. 4. *Top panel: Number of observations for each country used for estimation of the conditional TFR projection model, where the total number of observations is* 1007; *observations come from* 114 *countries and cover time periods* 1970–1975 *to* 2015–2020. *Bottom panel: TFR projections are created using the conditional TFR projection model for the* 83 *countries highlighted in blue.*

We considered five scenarios for intervention-based projections of educational attainment and contraceptive prevalence as inputs to the conditional TFR projection model. These scenarios are summarized in Table 1. The covariate projections were centered at their expected values, assuming no policy intervention, which ensures the intervention-based covariate projections reflect acceleration in trends beyond what we would expect if no intervention occurred. For example, in the nonintervention setting, women's educational attainment is projected to increase at the same pace that would occur assuming no intervention. Thus, the centered nonintervention projections of ΔLowSec+ are close to 0. In the SDG intervention scenarios, women's educational attainment is projected to increase at faster rates than would occur assuming no intervention. Correspondingly, the centered intervention-based projections of ΔLowSec+ are larger than 0. Further details of the methods used to construct the

TABLE 1
Summary of projection scenarios

Scenario	Target 4.1 assumptions	Target 3.7 assumptions
Reference	No intervention	No intervention
Both SDGs (0% Unmet)	Universal lower secondary education by 2030	Unmet need reaches 0% in 2030; all unmet need is assumed to be met with modern methods
Both SDGs (75% DS)	Universal lower secondary education by 2030	Demand satisfied by modern methods reaches 75% by 2030; all increases in contraceptive prevalence are assumed to be for modern methods
Both SDGs 2040 (75% DS)	Universal lower secondary education by 2040	Demand satisfied by modern methods reaches 75% by 2040; all increases in contraceptive prevalence are assumed to be for modern methods
Education SDG Only	Universal lower secondary education by 2030	No intervention

intervention-based covariate projections can be found in Section 2 of the Supplementary Material (Liu and Raftery (2024)).

First, we considered nonintervention projections of the covariates as our reference scenario. We note that TFR projections from the reference scenario are not expected to be identical to the projections produced by the U.N. for WPP 2019. However, the two sets of projections should be very similar, as the reference scenario was constructed to reflect the assumption of no additional policy intervention targeting education or family planning that is implicit in the WPP 2019 projections.

Next, we considered two scenarios corresponding to attaining SDG Targets 4.1 and 3.7 simultaneously in 2030. Both scenarios interpret achievement of Target 4.1 as attaining universal lower secondary education by 2030, following the implementation developed by Abel et al. (2016). Both scenarios also include the effect of achieving Target 4.1 on family planning, where increased educational attainment is assumed to increase demand for family planning. Where the two scenarios differ is in their implementations of Target 3.7. The first of these scenarios, labeled "Both SDGs (0% Unmet)," interprets Target 3.7 as meaning that unmet need for family planning will decline to zero in 2030. This scenario can be thought of as an upper bound on the possible effect the SDG intervention could have on TFR projections.

The second scenario, labeled "Both SDGs (75% DS)," interprets Target 3.7 as meaning that at least 75% of the demand for family planning in 2030 will be satisfied using modern methods. Demand satisfied using modern methods is defined as the ratio of contraceptive prevalence of modern methods to total demand, where total demand is the sum of total contraceptive prevalence and unmet need for family planning. This scenario follows the benchmark for achievement of Target 3.7 proposed by Fabic et al. (2015) and provides a more realistic interpretation of the effect that attaining the target might have on projections of contraceptive prevalence. The SDG intervention projections of contraceptive prevalence for this scenario were constructed following the accelerated transition method developed by Cahill, Weinberger and Alkema (2020) with some modifications.

We also considered a more gradual policy intervention in which the SDGs are achieved in 2040 rather than 2030, called "Both SDGs 2040 (75% DS)." This scenario follows the same implementation as the Both SDGs (75% DS) scenario, with the modification that the SDG targets are assumed to be met in 2040 instead of 2030. For many high-fertility countries, achieving the SDG targets in 2030 is highly ambitious (Abel et al. (2016), Friedman et al.

(2020)), so considering a scenario where the same goals are met a decade later may be viewed as a more realistic policy intervention.

Finally, we considered an "Education SDG Only" scenario where only SDG Target 4.1 is met in 2030 with no additional policy intervention for family planning. For the Education SDG Only scenario, the projection model was reestimated to include only education, GDP, and their interactions with the SSA indicator as covariates. Education is a less proximate cause of fertility decline than family planning, as seen in Figure 3. Reestimating the projection model without the family planning variable is necessary to ensure that the coefficient of education fully captures both the direct effect that education has on fertility and the indirect effect education has on fertility through the effect of education on family planning. By comparing results from the Education SDG Only scenario with results from the scenarios where both SDG targets are met, we were able to quantify the additional effect that meeting Target 3.7 would have on TFR projections.

For all intervention-based projection scenarios, we assumed that the policy efforts required to attain the SDGs in the target year (2030 or 2040) are sustained out to 2100.

TFR projections from the conditional TFR projection model are translated into population projections using the cohort-component method, as implemented in the "bayesPop" R package (Ševčíková and Raftery (2016)), which is based on the demographic balancing equation,

$$\text{Population}_{t+1} = \text{Population}_t + \text{Births}_t - \text{Deaths}_t + \text{Immigrants}_t - \text{Emigrants}_t,$$

where the population size at time $(t + 1)$ is equal to the population size at time t plus the number of births and number of immigrants occurring in time interval t to $(t + 1)$ and minus the number of deaths and number of emigrants occuring in time interval t to $(t + 1)$ (Preston, Heuveline and Guillot (2001)). The bayesPop package uses the cohort-component method of population projection, an age- and sex-specific version of the demographic balancing equation, to create age- and sex-specific population projections. Population projections were created using probabilistic projections of mortality and migration as inputs. Projections of mortality were created using the "bayesLifeHIV" R package[4] (Godwin and Raftery (2017)), and projections of migration were created following the method of Azose and Raftery (2015).

3. Results. Projections of TFR and population size from the conditional projection model are presented in this section for the five-year time periods from 2020–2025 to 2095–2100, using Nigeria as a case study. Projections of TFR and population size for sub-Saharan Africa are also presented. Additional projection results, including projections of population size for the regional aggregate of all countries for which we create intervention-based projections of TFR, are available in Sections 5 and 6 of the Supplementary Material (Liu and Raftery (2024)).

3.1. *Case study*: *Nigeria*. We present projections of TFR and population size, using Nigeria as a case study. Nigeria is one of the most important countries for projections of future world population, as it is a high-fertility country, with TFR in 2015–2020 of 5.42 children per woman, and is the most populous country in Africa, with estimated population size in 2020 of 206 million people.

Median projections of TFR and population for Nigeria are plotted for all projection scenarios in Figure 5. We also plot 95% projection intervals (PIs) for the reference and Both SDGs (0% Unmet) scenarios. Median and 95% PIs for projected values of TFR and population size for all scenarios are reported in Tables 2 and 3, where the projection intervals reflect both uncertainty about the parameters of the conditional TFR projection model and uncertainty about the future values of the covariates. Tables 2 and 3 also report differences in medians across the different projection scenarios for ease of comparison.

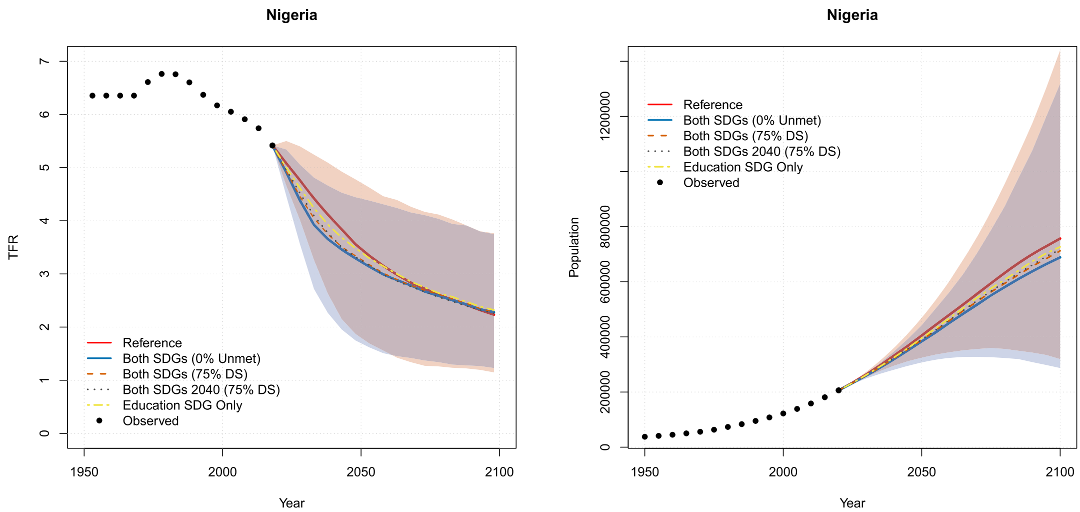

FIG. 5. *Comparison of median TFR and population projections for Nigeria from reference scenario in red, Both SDGs* (0% *Unmet*) *in dark blue, Both SDGs* (75% *DS*) *in orange dashed, Both SDGs* 2040 (75% *DS*) *in dark grey dotted, and Education SDG Only in yellow dash-dotted. Ninety-five percent projection intervals for the reference and Both SDGs* (0% *Unmet*) *scenarios are also plotted.*

In 2030–2035, the time period directly following the SDG intervention, the Both SDGs (0% Unmet) scenario projects TFR to be 3.92 children per woman with a 95% PI of (2.72, 4.81), while the Both SDGs (75% DS) scenario projects TFR to be 4.05 (2.90, 4.90) children per woman. This is a reduction of 0.50 and 0.37 of a child, respectively, from the reference scenario projection of 4.42 (3.26, 5.24) children per woman. These differences translate into differences in median population size projections of 8.3 and 6.5 million fewer people in 2035, respectively, compared to the reference scenario. The most extreme interpretation

TABLE 2
Median TFR projections in 2030–2035, 2045–2050, *and* 2095–2100 *for Nigeria in children per woman for all projection scenarios with* 95% *PIs. Rows indicating differences between projection scenarios show differences between median projected TFR*

	2030–2035	2045–2050	2095–2100
Reference	4.42 (3.26, 5.24)	3.56 (1.87, 4.78)	2.23 (1.15, 3.76)
Both SDGs (0% Unmet)	3.92 (2.72, 4.81)	3.29 (1.75, 4.44)	2.28 (1.23, 3.75)
Both SDGs (75% DS)	4.05 (2.90, 4.90)	3.34 (1.80, 4.54)	2.28 (1.23, 3.81)
Both SDGs 2040	4.10 (2.94, 4.95)	3.32 (1.77, 4.57)	2.26 (1.26, 3.80)
Educ SDG Only	4.24 (3.16, 5.02)	3.48 (1.97, 4.64)	2.32 (1.19, 3.74)
Reference—Both SDGs (0% Unmet)	0.50	0.27	−0.05
Reference—Both SDGs (75% DS)	0.37	0.22	−0.05
Reference—Both SDGS 2040	0.33	0.24	−0.02
Reference—Educ SDG Only	0.18	0.07	−0.09
Both SDGs (75% DS)—Both SDGs (0% Unmet)	0.13	0.05	0.00
Both SDGs 2040—Both SDGs (75% DS)	0.05	−0.02	−0.02
Educ SDG Only—Both SDGs (0% Unmet)	0.32	0.19	0.04
Educ SDG Only—Both SDGs (75% DS)	0.19	0.14	0.04

[4] Available at https://github.com/PPgp/bayesLifeHIV, downloaded on March 30, 2021.

TABLE 3
Median population projections in 2035, 2050, and 2100 for Nigeria in millions of people for all projection scenarios with 95% PIs. Rows indicating differences between projection scenarios show differences between median projected population size

	2035	2050	2100
Reference	297 (276, 315)	405 (325, 469)	757 (320, 1441)
Both SDGs (0% Unmet)	289 (266, 306)	384 (308, 443)	689 (287, 1319)
Both SDGs (75% DS)	290 (269, 308)	389 (312, 450)	712 (305, 1331)
Both SDGs 2040	292 (272, 308)	391 (317, 452)	717 (298, 1336)
Educ SDG Only	293 (274, 310)	396 (325, 458)	727 (326, 1411)
Reference—Both SDGs (0% Unmet)	8.3	21.0	68.4
Reference—Both SDGs (75% DS)	6.5	15.9	44.6
Reference—Both SDGS 2040	5.4	14.5	40.2
Reference—Educ SDG Only	3.9	9.1	30.3
Both SDGs (75% DS)—Both SDGs (0% Unmet)	1.8	5.1	23.7
Both SDGs 2040—Both SDGs (75% DS)	1.2	1.4	4.5
Educ SDG Only—Both SDGs (0% Unmet)	4.4	11.9	38.0
Educ SDG Only—Both SDGs (75% DS)	2.6	6.8	14.3

of the SDGs, Both SDGs (0% Unmet), leads to the largest reduction in projected TFR and population size out of all intervention scenarios in 2030–2035, while the more conservative interpretations of meeting the SDGs lead to smaller reductions in projected TFR and population size.

From the Education SDG Only scenario, we see that attaining Target 4.1 in 2030 in the absence of any policy intervention for family planning still leads to a reduction of 0.18 of a child in median projected TFR for Nigeria compared to the reference scenario in 2030–2035. This projection incorporates both the direct effect of attaining Target 4.1 on fertility and the indirect effect of attaining Target 4.1 on fertility through the effect of education on family planning. Comparing the differences between the Education SDG Only scenario with the scenarios where both SDG targets are met allows us to quantify the additional effect of policy interventions for family planning on fertility decline. For the different interpretations of Target 3.7, the additional effect of policy interventions targeting family planning corresponds to additional reductions in median projected TFR of 0.32 or 0.19 in 2030–2035, compared to only attaining Target 4.1.

In 2045–2050, TFR is projected to be 3.29 (1.75, 4.44) in the Both SDGs (0% Unmet) scenario and 3.34 (1.80, 4.54) in the Both SDGs (75% DS) scenario. Compared to the reference scenario projection of 3.56 (1.87, 4.78), this is a reduction of 0.27 and 0.22 of a child, respectively. These differences in TFR translate into differences in population size of 21.0 and 15.9 million fewer people, respectively, in 2050.

After midcentury TFR projections for all scenarios begin to converge. TFR projections in 2095–2100 range between 2.23 (1.15, 3.76) in the reference scenario, 2.28 (1.23, 3.75) in Both SDGs (0% Unmet), 2.28 (1.23, 3.81) in Both SDGs (75% DS), 2.26 (1.26, 3.80) in Both SDGs 2040 (75% DS), and 2.32 (1.19, 3.74) in Education SDG Only. This convergence is due to the shared post-transition Phase III model, where once a country has entered Phase III, the country is projected to converge toward and fluctuate around a long-term mean TFR. As TFR projections across all scenarios eventually converge to the same country-specific mean, the most interesting comparisons of the projected effects of the SDG interventions refer to the period before mid-century.

Despite the convergence in TFRs, population projections remain relatively distinct across the projection scenarios out to 2100 due to population momentum. In 2100, Nigeria's population is projected to reach 757 (320, 1441) million people under the reference scenario. In the Both SDGs (0% Unmet) scenario, population is projected to reach 689 (287, 1319) million, which is a reduction of 68.4 million people compared to the reference scenario. In the Both SDGs (75% DS) scenario, population is projected to reach 712 (305, 1331) million, which is a reduction of 44.6 million people compared to the reference scenario. In the Both SDGs 2040 (75% DS) scenario, population is projected to be 717 (298, 1336) million in 2100, which is a reduction of 40.2 million people compared to the reference scenario. We note that the projected distributions of population in 2100 are very similar for the Both SDGs (75% DS) and Both SDGs 2040 (75% DS) scenarios, with substantial overlap between their 95% PIs. This overlap is unsurprising, given the similarities of the TFR projections for these scenarios and the convergence of TFR projections across all scenarios after midcentury. However, it is still notable, as it suggests meeting the SDGs a decade later than the target year of 2030 could lead to similar long-term reductions in population growth for Nigeria as meeting the SDGs in 2030.

For Nigeria the 95% PIs for population projections from the Education SDG Only scenario overlap significantly with the reference scenario projections. In 2100, population is projected to reach 727 (326, 1411) million people under Education SDG Only, compared to the reference scenario's projected 757 (320, 1441) million people. This still corresponds to a difference in median projected population size of 30.3 million people, but the boundaries of the 95% PI for the Education Only SDG scenario lie entirely within the boundaries of the 95% PI for the reference scenario. The large overlap suggests that, while policy interventions targeting educational attainment in the absence of interventions for family planning may still result in some reductions in population size for Nigeria, there is also the possibility of negligible long-term impacts on population size compared to the reference scenario.

3.2. *Sub-Saharan Africa.* Next, we present projection results for sub-Saharan Africa as a whole. World population in the next century will be driven by population growth in high-fertility countries, the majority of which are in SSA. As described in Section 2.5, TFR projections for countries with current TFR ≥ 2.1 follow the conditional TFR projection model, while countries that currently have lower fertility are projected with the bayesTFR model. Countries without available covariate data are also projected using the bayesTFR model. Thus, our intervention-based projections of regional aggregates reflect only the impact of policy interventions in countries with TFR above replacement level that had available covariate data. For SSA there are 41 countries that are projected using the conditional TFR projection model and nine countries that are projected using the bayesTFR model.

Figure 6 shows median projections of TFR and population for SSA for all projection scenarios alongside 95% PIs for the reference and Both SDGs (0% Unmet) scenarios. Median and 95% PIs for projected values of TFR for SSA for all scenarios and differences in median projected TFR between different projection scenarios are shown in Table 4 for 2030–2035, 2045–2050, and 2095–2100. TFR results were aggregated for SSA as the average of the age-specific fertility rates for countries in SSA, weighted by the size of the female population for each country.[5] Table 5 summarizes the population projections corresponding to the TFR projection scenarios for SSA.

In 2030–2035, the Both SDGs (0% Unmet) scenario projects TFR to be 3.27 (2.77, 3.79) children per woman in SSA while the Both SDGs (75% DS) scenario projects TFR to be 3.38 (2.91, 3.85) children per woman. This is a reduction in medians of 0.55 and 0.44 of a child,

[5]Note that is not the exact TFR for SSA but is likely to be a very close approximation.

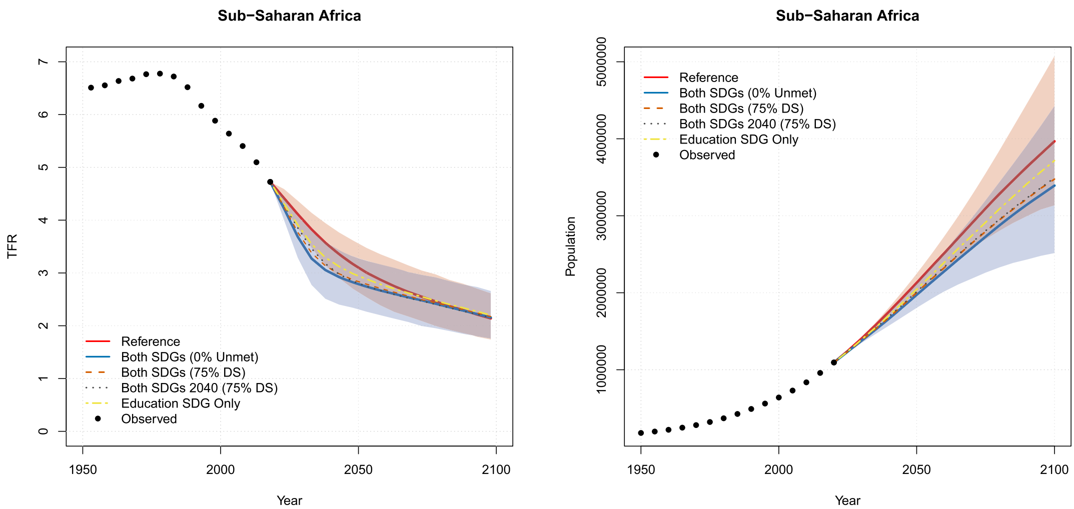

FIG. 6. *Comparison of median TFR and population projections for sub-Saharan Africa from reference scenario in red, Both SDGs (0% Unmet) in dark blue, Both SDGs (75% DS) in orange dashed, Both SDGs 2040 (75% DS) in dark grey dotted, and Education SDG Only in yellow dash-dotted. Ninety-five percent projection intervals for the reference and Both SDGs (0% Unmet) scenarios are also plotted.*

respectively, from the reference scenario projection of 3.83 (3.48, 4.14). From the Education SDG Only scenario, attaining Target 4.1 in 2030 in the absence of any policy intervention for family planning leads to a reduction of 0.28 in median projected TFR compared to the reference scenario in 2030–2035. The additional effect of policy interventions for family planning leads to an additional reduction in median projected TFR of 0.27 or 0.17 for the different interpretations of Target 3.7.

In 2045–2050, the TFR for SSA is projected to be 2.82 (2.34, 3.31) in the Both SDGs (0% Unmet) scenario and 2.87 (2.38, 3.39) in the Both SDGs (75% DS) scenario. Compared to the reference scenario projection of 3.17 (2.70, 3.62), this is a reduction of 0.35 and 0.30 of a

TABLE 4
Median TFR projections in 2030–2035, 2045–2050, and 2095–2100 for sub-Saharan Africa in children per woman for all projection scenarios. Rows indicating differences between projection scenarios show differences between median projected TFR

	2030–2035	2045–2050	2095–2100
Reference	3.83 (3.48, 4.14)	3.17 (2.70, 3.62)	2.14 (1.74, 2.62)
Both SDGs (0% Unmet)	3.27 (2.77, 3.79)	2.82 (2.34, 3.31)	2.16 (1.76, 2.66)
Both SDGs (75% DS)	3.38 (2.91, 3.85)	2.87 (2.38, 3.39)	2.17 (1.75, 2.70)
Both SDGs 2040	3.46 (3.04, 3.89)	2.84 (2.34, 3.35)	2.15 (1.75, 2.66)
Educ SDG Only	3.55 (3.09, 3.98)	2.99 (2.51, 3.46)	2.20 (1.77, 2.69)
Reference—Both SDGs (0% Unmet)	0.55	0.35	−0.02
Reference—Both SDGs (75% DS)	0.44	0.30	−0.04
Reference—Both SDGS 2040	0.36	0.33	−0.02
Reference—Educ SDG Only	0.28	0.18	−0.06
Both SDGs (75% DS)—Both SDGs (0% Unmet)	0.11	0.05	0.02
Both SDGs 2040—Both SDGs (75% DS)	0.08	−0.03	−0.02
Educ SDG Only—Both SDGs (0% Unmet)	0.27	0.16	0.04
Educ SDG Only—Both SDGs (75% DS)	0.17	0.12	0.03

TABLE 5

Median projections in 2035, 2050, and 2100 of population size for sub-Saharan Africa in millions of people for all projection scenarios with 95% PIs. Rows indicating differences between projection scenarios show differences between median projected population size

	2035	2050	2100
Reference	1576 (1541, 1609)	2129 (2001, 2247)	3967 (3135, 5074)
Both SDGs (0% Unmet)	1518 (1462, 1569)	1973 (1801, 2121)	3392 (2515, 4427)
Both SDGs (75% DS)	1528 (1476, 1579)	2003 (1840, 2151)	3476 (2694, 4572)
Both SDGs 2040	1539 (1494, 1582)	2013 (1870, 2153)	3493 (2724, 4496)
Educ SDG Only	1546 (1496, 1592)	2044 (1894, 2197)	3716 (2887, 4738)
Reference—Both SDGs (0% Unmet)	57	156	575
Reference—Both SDGs (75% DS)	47	126	491
Reference—Both SDGS 2040	36	115	474
Reference—Educ SDG Only	30	85	251
Both SDGs (75% DS)—Both SDGs (0% Unmet)	10	30	84
Both SDGs 2040—Both SDGs (75% DS)	11	10	17
Educ SDG Only—Both SDGs (0% Unmet)	27	72	324
Educ SDG Only—Both SDGs (75% DS)	17	41	240

child, respectively. Attaining Target 3.1 in 2030, in the absence of any policy intervention for family planning, leads to a reduction of 0.18 of a child, and the additional effect of attaining Target 3.7 leads to a reduction of 0.16 or 0.12 of a child for the different interpretations of the family planning target.

After midcentury we note the same convergence in TFR projections across projections scenarios that was observed in Nigeria. The TFR of SSA is projected to approach replacement level in 2095–2100 in all projection scenarios, with the slowest approach occurring in the Education SDG Only scenario. Population in 2100 in SSA is projected to reach 3.97 (3.14, 5.07) billion people in the reference scenario, 3.39 (2.52, 4.43) billion people in the Both SDGs (0% Unmet) scenario, 3.48 (2.69, 4.57) billion people in the Both SDGs (75% DS) scenario, 3.49 (2.72, 4.50) billion people in the Both SDGs 2040 (75% DS) scenario, and 3.72 (2.89, 4.74) billion people in the Education SDG Only scenario.

Population in 2100 is projected to be 575 million people lower in the Both SDGs (0% Unmet) scenario and 491 million people lower in the Both SDGs (75% DS) scenario than the reference scenario. If the SDGs are instead met in 2040, this difference is 474 million people. We note that the projected distributions for TFR and population size for the Both SDGs (75% DS) and Both SDGs 2040 (75% DS) scenarios are very similar across time periods. The difference between median TFR projections between these two scenarios is largest at about 0.08 of a child in 2030–2035, but the projected TFR distributions become nearly indistinguishable for 2045–2050 and 2095–2100. This suggests that achieving the SDG targets a decade later in countries that are not currently on track to meet the SDGs in 2030 could still have substantial long-term demographic implications for SSA.

In 2100, if only the target of universal lower secondary education is attained with no intervention targeting family planning, population is projected to be 251 million people lower than the reference scenario for SSA. The additional effect of attaining the SDG corresponding to family planning is a reduction of 324 million people in 2100 if Target 3.7 is interpreted as 0% Unmet Need and 240 million people if the target is interpreted as 75% Demand Satisfied.

4. Validation. Our goal in developing the conditional TFR projection model is not to improve the predictive performance of the existing bayesTFR projection method but to expand the utility of the method to allow for creation of policy-based intervention projections. The conditional TFR projection model should ideally extend the utility of the bayesTFR model for intervention scenario projections without reducing the predictive accuracy of bayesTFR. To evaluate this, the conditional TFR projection model was assessed using out-of-sample validation. Out-of-sample validation is a method frequently used to validate probabilistic forecasts and, in particular, was the method used to validate the original bayesTFR method (Alkema et al. (2011)). The validation exercises conducted on the conditional TFR projection model are compared to an analogous exercise for bayesTFR to ensure the conditional TFR projection model has similar predictive performance to bayesTFR.

For the first out-of-sample validation exercise, we created projections for the five-year time period 2015–2020 using the conditional projection model estimated using data spanning 1970–1975 through 2010–2015. Fertility observations came from WPP 2019 and were subject to the same "high-fertility" constraint as before, where only country-time pairs where the country was in Phase II and had TFR > 2.5 were included in estimation of the second stage. Covariate data were restricted to reflect the true data availability before 2015 as much as was possible for both estimation and projection. We used data from Version 1.2 of the Wittgenstein Centre Data Explorer to fit the educational attainment model to create out-of-sample estimates and projections of ΔLowSec+. For estimates and projections of contraceptive prevalence, the FPEMglobal model was reestimated using only survey estimates that were available before 2015. The model for GDP was also reestimated using only data that were available in the 1970–1975 through 2010–2015 estimation period. This first validation exercise checks the marginal predictive performance of the conditional TFR projection model, where we expect the conditional model to perform similarly to bayesTFR.

For the second validation exercise, we considered out-of-sample validation conditional on knowing the true values of the covariates for 2015–2020. The projection model was estimated using the same method as the first out-of-sample exercise, where the model is estimated leaving out data for the 2015–2020 time period. TFR for 2015–2020 is projected using the left-out 2015–2020 values of the covariates as inputs. This second validation exercise checks the conditional predictive performance of the conditional TFR projection model, where we expect the conditional model to perform similarly or slightly better than bayesTFR.

The results of the two validation exercises are summarized in Table 6, where the results for the conditional TFR projection model are compared with analogous results for bayesTFR. Results for both models are averaged over the 97 countries included in the out-of-sample estimation. The out-of-sample validation exercises using the out-of-sample projections of the covariates are denoted "OOS" in the "Validation Type" column, while the conditional out-of-sample validation using the left-out 2015–2020 values of the covariates is denoted "Conditional OOS." The root mean squared error (RMSE) evaluates the performance of the

TABLE 6

Out-of-sample (*OOS*) *validation results for one five-year time period* (2015–2020) *left out for the conditional TFR projection model and bayesTFR using WPP* 2019, *where results are averaged across all* 97 *countries included in estimation of the second stage. The metrics shown are the root mean squared error* (*RMSE*), *the coverage of the* 95% *projection intervals* (95% *Cvg*), *and the average width of the* 95% *projection intervals* (95% *Width*)

Model	Validation type	RMSE	95% Cvg	95% Width
Conditional Projection Model	OOS	0.1234	0.9691	0.8318
Conditional Projection Model	Conditional OOS	0.1197	0.9691	0.8033
bayesTFR		0.1215	0.9691	0.8046

point predictions and is calculated as

$$\sqrt{\frac{1}{97}\sum_{c}(\hat{f}_{c,2015-2020} - f_{c,2015-2020})^2},$$

where $\hat{f}_{c,2015-2020}$ denotes the median projection of TFR for country c and time 2015–2020, $f_{c,2015-2020}$ is the observed value of TFR for country c and time 2015–2020 from WPP 2019, and the sum is taken over all 97 countries included in the out-of-sample estimation. The conditional TFR projection model performed similarly to bayesTFR in terms of RMSE in both validation exercises. The OOS validation exercise resulted in slightly larger RMSE, compared to bayesTFR, while the Conditional OOS validation exercise resulted in slightly smaller RMSE compared to bayesTFR.

The performance of the projection intervals was evaluated by computing the coverage of the 95% projection intervals with respect to the left-out observations, where coverage is averaged over all 97 countries and is calculated as the proportion of the intervals that contained the true 2015–2020 value of TFR from WPP 2019. The conditional TFR projection model performed similarly to bayesTFR, with both projection models having coverage for the 95% intervals slightly above the nominal level. The projection intervals were also evaluated by looking at the average interval width across all countries. The intervals for the Conditional OOS validation exercise were very similar in width to the bayesTFR intervals, but the intervals for the OOS validation exercise were wider on average than the intervals from bayesTFR. This follows expectations, as the OOS validation exercise incorporates uncertainty about the out-of-sample covariate projections into the projections of TFR. Based on these validation exercises and comparisons to bayesTFR, we find the conditional TFR projection model has similar predictive performance as bayesTFR. Thus, the conditional TFR projection model is able to extend the utility of bayesTFR by enabling the creation of conditional projections based on policy intervention scenarios without sacrificing the predictive accuracy of bayesTFR.

We also conducted a sensitivity analysis for the prior distributions of the $\boldsymbol{\beta}$ coefficients and found that the conditional TFR projection model is not sensitive to changes in the prior distributions. Further details of this analysis and other validation exercises, including checking of the conditional linearity assumption, can be found in Section 4 of the Supplementary Material (Liu and Raftery (2024)).

5. Discussion. We created a conditional projection model for TFR that extends the unconditional Bayesian hierarchical model that is the basis of the fertility projections published by the U.N.. The conditional TFR model enables the creation of probabilistic projections of TFR conditional on policy interventions that target educational attainment and contraceptive prevalence, such as meeting the SDG targets for education and family planning.

Previous work has explored potential ways to quantify the possible impact of the SDGs on fertility and population size. We compare our results with those of Abel et al. (2016) and Vollset et al. (2020). Abel et al. (2016) created population projections based on attaining the SDGs by building upon the population projection model developed by the Wittgenstein Centre. The Wittgenstein Centre projections are based on global population scenarios corresponding to the Shared Socioeconomic Pathways (SSPs) used by the Intergovernmental Panel on Climate Change (Lutz, Butz and KC (2014)). In lieu of reporting population projections with corresponding measures of uncertainty, the Wittgenstein Centre produces population projections following a number of different SSP scenarios corresponding to different levels of socioeconomic development.

Abel et al. (2016) extends this work to consider different SDG scenarios based on varying interpretations of the SDG targets. In particular, Target 4.1 is interpreted as either universal lower secondary education or universal upper secondary education, and Target 3.7 is interpreted as meaning that education-specific fertility rates will either be 20% lower or 10% lower due to reductions in unmet need for family planning. These different SDG scenarios lead to a range of possible population projections. However, the individual SDG scenario projections do not come with measures of uncertainty.

Vollset et al. (2020) created probabilistic population projections for the Global Burden of Disease (GBD) project at IHME. The GBD model incorporates measures of education and family planning as covariates in the fertility projection model and incorporates uncertainty in projections. The GBD model projects completed cohort fertility at age 50 as a function of educational attainment (measured as years of education) and contraceptive met need. Vollset et al. consider scenarios for population projections based on different rates of change in educational attainment and contraceptive met need, including a scenario corresponding to meeting the SDGs.

Unlike the Abel et al. (2016) projections, the Vollset et al. (2020) projections do come with measures of uncertainty. However, the Vollset et al. projections have been criticized in the demographic community for questionable model assumptions and demographically implausible projection results (Gietel-Basten and Sobotka (2021, 2020)). The interpretation of their intervention-based projections as causal has also been questioned by Alkema (2020), who highlighted a key flaw in the causal assumptions underlying the Vollset et al. model. By using met need for contraception as the measure of family planning, the Vollset et al. model does not distinguish between the effect of increased demand for family planning and the effect of improved access among those with a need for family planning in their SDG intervention scenario. We avoided this issue in our model by focusing on the relationship between contraceptive prevalence and fertility. In our model, increases in contraceptive prevalence that result from the SDG intervention correspond both to fertility reductions that are due to increases in demand for family planning and fertility reductions that are due to improved access. These two pathways leading to fertility reductions are also reflected in our implementation of the SDG intervention projections for contraceptive prevalence.

There are notable differences between our results and the two existing sets of intervention-based projections. We compare population size projections under reference and SDG intervention scenarios from our model, the Abel et al. model, and the Vollset et al. model for the regional aggregate of a subset of 72 out of the 83 countries for which we create intervention-based projections. We exclude 11 countries from the comparison due to lack of available projections for the Abel et al. model. The countries additionally excluded are Afghanistan, Angola, Bolivia, Botswana, Côte d'Ivoire, Israel, Oman, Sri Lanka, Sudan, Togo, and Yemen.

We are unable to directly compare the median population projections for the regional aggregate of the 72 countries across models, as Abel et al. (2016) and Vollset et al. (2020) do not publish individual projection trajectories. Instead, we compare an approximation for the median projected population of the regional aggregate. For the Abel et al. model, we approximate the median projected population for the regional aggregate with the sum of the (deterministic) population projections for each country in the aggregate. The SDG scenario projections for Abel et al. correspond to their SDG2 projection scenario,[6] while the reference scenario projections correspond to the SSP2 projection scenario.[7] For our model and the Vollset et al. model, we approximate the median projected population for the regional

[6]Population projections for individual countries were obtained from the Supplementary Material to Abel et al. (2016), available at https://www.iiasa.ac.at/SDGscenarios2016 and downloaded on February 8, 2023.

[7]Population projections for individual countries were obtained from version 1.2 of the Wittgenstein Centre Data Explorer, available at http://dataexplorer.wittgensteincentre.org/wcde-v1/ and downloaded on February 8, 2023.

TABLE 7

Comparison of sum of median population projections for the regional aggregate of 72 countries in 2050 and 2100 under the reference model, the intervention scenario assuming both SDG targets are met in 2030, and the difference between the two scenarios from our conditional projection model (Cond. BHM), Abel et al. (2016), and Vollset et al. (2020) in billions of people. The SDG results from our conditional projection model follow the Both SDGs (0% Unmet) and Both SDGs (75% DS) scenarios. The SDG results from the Abel et al. model follow their SDG2 scenario

Year	Scenario	Cond. BHM (0% Unmet)	Cond. BHM (75% DS)	Abel et al. (2016)	Vollset et al. (2020)
	Reference	5.52	5.52	5.02	5.42
2050	SDG	5.17	5.23	4.66	4.82
	Difference	0.35	0.28	0.36	0.60
	Reference	7.01	7.01	5.41	5.61
2100	SDG	5.98	6.17	4.66	3.73
	Difference	1.03	0.84	0.76	1.88

aggregate using the sum of the median population projections for each country in the aggregate.[8] The sum of median population projections over all countries in the aggregate is not equivalent to the median of the projected population distribution for the regional aggregate, but for our model we found the sum of medians to be a good approximation. Additional details of this approximation can be found in Section 7 of the Supplementary Material (Liu and Raftery (2024)).

Table 7 summarizes a comparison of the reference scenario and SDG intervention scenario population projection results from our model, the Abel et al. model, and the Vollset et al. model for the regional aggregate of 72 countries. SDG intervention results from our conditional projection model are shown for the Both SDGs (0% Unmet) and Both SDGs (75% DS) projection scenarios, where Both SDGs (0% Unmet) aligns most closely with the SDG assumptions used by Abel et al. and Vollset et al. Results from Both SDGs (75% DS) are included in the comparison to illustrate a more realistic interpretation of meeting the SDGs.

We note that there can be large differences between our reference scenario projections and those from Abel et al. (2016) and Vollset et al. (2020), particularly for 2100. One source of these differences is the input data used to estimate the three models. Our model and the Abel et al. model use similar sources of data; however, Abel et al. use older versions of these sources of data. In particular, both our model and the Abel et al. model use estimates and projections of educational attainment from the Wittgenstein Centre. However, the Abel et al. results are based on the 2014 version of the educational attainment data while our results are based on the 2018 update. The older version of the Wittgenstein Centre database covers fewer countries, uses an earlier baseline year of data, and has some differences in methodology used for reconstruction of past educational attainment (Speringer et al. (2019)).

There are also notable differences between the data used to estimate the Vollset et al. model and the data used to estimate our model. The Vollset et al. model uses estimates of past fertility from the GBD study at IHME, whereas our model is based on estimates from the U.N.. One important difference between these two sets of fertility estimates concerns SSA, where the estimates of fertility for countries in SSA from IHME tend to be lower than the estimates from the U.N. (Gietel-Basten and Sobotka (2020)). As countries in SSA account

[8]Reference and SDG scenario population projections for individual countries from Vollset et al. (2020) are available at https://ghdx.healthdata.org/record/ihme-data/global-population-forecasts-2017-2100, downloaded on February 8, 2023.

for about half of the countries in the regional aggregate, this impacts the overall reference scenario comparisons.

Another source of the differences between projections across the three models is the underlying differences in fertility projection assumptions in the low-fertility setting when TFR has reached below 2.1 children per woman. These low-fertility assumptions dictate the long-run fertility levels used to model the posttransition phase, which mostly impacts the population projections for countries in the regional aggregate in the latter half of the century. As our analysis is primarily conducted in the high-fertility setting and we use the post-transition projection model from bayesTFR without any modifications, details of these low-fertility modeling differences are out of the scope of this paper but have been discussed by Wilmoth (2019), Vollset et al. (2020), and Kaneda, Falk and Patierno (2021), among others.

Due to these differences in reference scenario projections, we focus our comparisons on the projected differences between the reference scenario and the SDG intervention scenario from each set of projections. These projected differences are shown in the rows labeled "Difference" in Table 7 for 2050 and 2100. Additional comparisons of the projected differences for all projection years can be found in Section 7 of the Supplementary Material (Liu and Raftery (2024)).

We first consider comparisons between our results and the Abel et al. (2016) results. The assumptions of the SDG2 scenario from Abel et al. align most closely with our Both SDGs (0% Unmet) scenario. Compared to Abel et al., we project larger reductions in population size in 2100 due to attaining both SDGs in 2030. Under SDG2 Abel et al. project the population of the regional aggregate to be 4.657 billion people in 2100, which is a reduction of 755 million people, compared to their reference scenario projection of 5.412 billion people. In contrast, we project a reduction from 7.010 billion people to 5.984 billion people between our reference and Both SDGs (0% Unmet) scenarios, which is a difference of 1.026 billion people. The differences in projection results between our model and the Abel et al. model are much smaller in 2050. Our Both SDGs (0% Unmet) scenario projects a reduction from 5.516 billion people to 5.166 billion people, which is a difference of 350 million people from meeting the SDGs. The Abel et al. model projects a very similar difference of 360 million people in 2050 from meeting the SDGs, with a reference scenario population of 5.022 billion people and an SDG intervention scenario population of 4.662 billion people.

The projected reductions in population size from our Both SDGs (0% Unmet) scenario roughly agree with the projected reductions in population size from Abel et al. up until midcentury, at which point the projected reductions diverge. A large part of the differences in the projected effect of the SDGs after midcentury is due to underlying differences between the fertility projection models used by the U.N. and the Wittgenstein Centre. Abel et al. project the population of the regional aggregate to peak slightly after midcentury in both the reference and SDG intervention scenarios, whereas our population projections continue to increase to 2100 in all scenarios. We note that the differences in projected reductions in population between our more realistic Both SDGs (75% DS) scenario and the Abel et al. projections are less pronounced, with the largest difference occurring at 2100. However, the two sets of projections are fairly similar, even at 2100, with our model projecting a reduction of 835 million people and the Abel et al. model projecting a reduction of 755 million people.

Next, we consider comparisons with Vollset et al. (2020). The assumptions of the SDG intervention projection scenario from Vollset et al. also align most closely with our Both SDGs (0% Unmet) scenario. Vollset et al. found that meeting the SDG targets for education and contraceptive met need would result in population size in 2100 for the regional aggregate of 3.730 billion people, compared to their reference scenario projection of 5.612 billion people which is a reduction in population of 1.882 billion people. In comparison, we project a smaller reduction of 1.026 billion people in 2100 from our Both SDGs (0% Umet) scenario.

Similar differences between the Vollset et al. projections and our projections occur in earlier time periods. In 2050, Vollset et al. projects population to be 5.418 billion people in the reference scenario and 4.820 billion people in the SDG intervention scenario, which is a difference of 598 million people. In our Both SDGs (0% Unmet) scenario, we project a smaller difference of 350 million people.

The projected reductions in population from Vollset et al. are much larger than the projected reductions from our results and from Abel et al. By 2100, the projected reduction in population from Vollset et al. is about 1.83 times as large as the projected reduction in population from our Both SDGs (0% Unmet) scenario and about 2.25 times as large as the projected reduction from our Both SDGs (75% DS) scenario. Part of the differences between our projections and the Vollset et al. projections are due to underlying differences in fertility model assumptions. Vollset et al. project the population of the regional aggregate to peak around or slightly after midcentury in both reference and SDG scenarios, whereas our population projections continue to increase to 2100. A comparison of the reference scenario projections for world population from the GBD model, the Wittgenstein Centre model, and the U.N. model was conducted in Vollset et al. (2020). They found that for the world aggregate, the GBD projections align more closely with the results from the Wittgenstein Centre than with results from the U.N. for both fertility and population projections. However, despite these similarities in reference scenario projections, it is notable that Vollset et al. project the effect of meeting the SDGs for the regional aggregate to be about 1.66 times the effect projected by Abel et al. in 2050 and almost 2.5 times the effect projected by Abel et al. in 2100.

Our method improves upon the existing intervention-based projections of TFR and population in several ways. First, unlike the Abel et al. model, our model fully incorporates uncertainty about covariate projections into projections of TFR and provides probabilistic projections of TFR and population size. Second, unlike the Vollset et al. model, our model incorporates demographic background knowledge to ensure that results are demographically plausible and to inform the causal framework underlying the model.

Our projections also reflect only the impact of policy interventions in the high-fertility setting. While the accelerating effect of education and family planning expansion on fertility decline is well established in the high-fertility context, the effect is less clear in the low-fertility context, in particular for education. Although there is some evidence that the effect of education on fertility persists over the course of the fertility transition (Lutz, Butz and KC (2014)), there is also evidence that the effect of education may be different in countries where a majority of women have attained tertiary education (Asderá (2017b)). For example, there is evidence to suggest that the relationship between education and fertility may, in fact, be reversed in the low-fertility setting, where higher-educated women have greater resources to attain their desired childbearing and thus have higher fertility compared to lower-educated women (Sobotka, Beaujouan and Bavel (2017)). This uncertainty about the long-run relationship between education and fertility decline once a country reaches low fertility levels is not reflected in either the Abel et al. or Vollset et al. projections.

Unlike the existing projection models, our model also accounts for the fact that the associations between the covariates and fertility decline have been observed to be weaker in SSA, compared to other regions of the world. This difference is especially important in the context of intervention-based projections, where, for example, the effect of eliminating unmet need for family planning may have a weaker effect on fertility decline in SSA, compared to other regions of the world, due to high ideal family sizes (Bongaarts and Casterline (2013)).

Despite these improvements on the existing SDG intervention-based projections, our results have several limitations. The policy intervention scenarios rely on statistical extrapolation for projections of educational attainment and contraceptive prevalence. The SDG projections of the covariates are extreme scenarios, where the amount of acceleration in educational attainment and contraceptive prevalence encoded in the SDG intervention projections has not been observed historically. The intervention scenarios also assume that the historical relationships between education, family planning, and fertility will hold in the extrapolation, which may not be the case. This limitation is shared with all existing SDG intervention projections and, indeed, is acknowledged by both Abel et al. (2016) and Vollset et al. (2020).

Our projections are also limited in terms of interpretation as causal effects due to the simplifying assumptions needed to model the complex causal relationships between education, family planning, and fertility. The assumptions used in our model are outlined in Section 2.3 and are based on demographic background knowledge. However, this does not preclude the possibility that our model omits confounders or overly simplifies the underlying causal structure. The accuracy of our projections is further limited by the accuracy of the estimates and projections of the covariates. We used the best data available for globally and historically comparable estimates and projections of the covariates, but these still have limitations. For example, the estimates of contraceptive prevalence used in our model do not take the effectiveness of different contraceptive methods into account, which Bongaarts (2017) identifies as a key aspect of analyzing the relationship between contraceptive prevalence and TFR.

The proposed conditional TFR projection model is additionally constrained to the five-year time scale. This restriction is primarily due to the availability of the educational attainment data, where estimates of historical educational attainment from the Wittgenstein Centre are only available in five-year increments and the projection model for educational attainment was developed under the assumption of five-year increments. Due to this constraint, we used estimates of TFR from the 2019 revision of the U.N. *World Population Prospects*, which uses a five-year time scale, rather than the more recent 2022 revision, which uses a one-year time scale. Extending the conditional TFR projection methodology to the one-year time scale is of interest for future work. This could be done by building upon the one-year extension of the bayesTFR model developed by Liu, Ševčíková and Raftery (2023) and would ideally use one-year estimates and projections of all covariates, including educational attainment from the Wittgenstein Centre.

Finally, our population projection results assume that the SDG intervention scenarios affect population size only through the impact of the interventions on fertility. All population projections are created using nonintervention projections of mortality and migration. The potential impacts of universal secondary education and universal access to family planning on mortality and migration are not known to be substantial and seem likely to be much smaller than the effects on fertility.

6. Conclusion.

We have developed a conditional Bayesian hierarchical model for projections of TFR that incorporates the effect of women's educational attainment, contraceptive prevalence, and GDP per capita. This model creates probabilistic projections of TFR conditional on projections of the covariates, where the covariate projections can correspond to policy intervention outcomes. These conditional TFR projections could be used to answer questions about the likely effect of education and family planning policies on future fertility and could be an informative tool for policymakers in high-fertility countries. Given a specific policy-based intervention scenario, the TFR and population projections resulting from the conditional TFR projection model could help policymakers plan for the future infrastructure needs of their constituencies such as schools, health care, and transportation. This, in turn, could be used to determine the allocation of resources in support of expanding girls' education and expanding access to family planning.

As an illustrative policy intervention, we focused on attaining the SDG Targets 3.7 and 4.1, which target universal access to family planning and universal secondary education, respectively. We created projections of TFR for five-year time periods covering 2020–2025 to

2095–2100, conditional on several policy-based intervention scenarios for differing rates of increase in educational attainment and contraceptive prevalence corresponding to different translations of the SDG targets. Using the intervention-based projections of TFR, we created corresponding probabilistic projections of population size for each intervention scenario.

One potential use of the conditional projection results could be to determine the relative allocation of resources to support girls' education and to support expansion of voluntary family planning programs through comparing the projected outcomes from the Education SDG Only scenario with the scenarios that assume both SDGs targets are met, such as the Both SDGs (75% DS) scenario. For sub-Saharan Africa, population size in 2100 is projected to reach 3.72 (2.89, 4.74) billion people under the Education SDG Only scenario, 3.48 (2.69, 4.57) billion people under the Both SDGs (75% DS) scenario, and 3.97 (3.14, 5.07) billion people in the reference scenario. While these results suggest notable acceleration in fertility decline can result from rapid expansion of educational attainment, it is likely that the combination of expansion of education *and* expansion of access to family planning is required to see the full effect of meeting the SDGs on future fertility and population size. Reaching the target of universal lower secondary education in 2030 in the absence of increased investment in family planning corresponds to a reduction in median projected population size for sub-Saharan Africa in 2100 of 251 million people. If the target of reaching 75% of demand for family planning satisfied by modern methods is also met in 2030, this corresponds to an additional reduction of 240 million people. Based on the median projections, about half of the potential reduction in population size in 2100 from meeting SDG Targets 4.1 and 3.7 can be attributed to the effect of meeting the education target and about half can be attributed to the effect of meeting the family planning target. These results indicate that expanding education for girls is a worthwhile policy goal to pursue on its own that, in addition to having other benefits to society, can contribute to accelerated fertility decline and a reduction in population growth. However, if accelerating fertility decline is a key policy goal, this comparison also suggests that increased access to family planning is a worthwhile investment.

Another potential application for the conditional TFR projection model is in supporting arguments for a slower, possibly more realistic expansion of education and family planning to achieve SDG Targets 4.1 and 3.7 in a later year. For many currently high-fertility countries, meeting these SDG targets in 2030 may be an unrealistic goal. We found that meeting the SDG targets a decade later in 2040 could still have substantial impacts on the future trajectory of TFR and population size. For sub-Saharan Africa, we found the median population size in 2100 in the Both SDGs (75% DS) scenario is projected to be 3.48 billion people with a 95% PI of (2.69, 4.57). If the same policy goals are met a decade later in 2040, population in 2100 is instead projected to be 3.49 (2.72, 4.50) billion people. Compared to the reference scenario, both of these intervention scenarios correspond to a reduction in median projected population in 2100 of over 470 million people. While meeting the SDGs in 2030 does lead to a larger reduction in projected median population in 2100, there is a substantial overlap between the projected population distributions for meeting the SDGs in 2030 or in 2040. The results from the conditional TFR projection model show that a sustained, slower investment over a longer time period could have comparable long-term effects on fertility and population size as a shorter-term, larger investment in education and family planning while also being more realistic to achieve.

Conditional TFR projections could be of use not only within the context of empowering women and girls and expanding the ability for individuals to achieve their desired childbearing goals but also for policymakers to consider more generally in conversations about sustainable development. The negative environmental impact of rapid population growth is well documented (e.g., O'Neill et al. (2010), Bongaarts (2016), Lutz (2023)), and policy discussions related to environmental sustainability and climate change must necessarily take information about future population size into account. The population projections created using the conditional TFR projections could help guide these discussions by providing a probabilistic view of what future population might look like under different education and family planning intervention scenarios. These intervention-scenario-based projections of population could then be translated into potential futures regarding long-term issues like food production, carbon emissions, and climate change. In turn, these discussions regarding sustainable development could provide a further rationale for increased investment in education and family planning.

Our findings suggest that attainment of SDG Targets 3.7 and 4.1 are likely to have substantial long-term effects on fertility decline and population growth in the high-fertility setting. Notable reductions in population growth are projected to occur, even if the targets are met a decade later than the target achievement date of 2030 and even if increased investment in girls' education occurs without increased investment in family planning programs. These results show that pursuit of the SDGs, even at a slower pace than implied by the target year of 2030, is a worthwhile policy goal that could result in substantial shifts in future demographic trends.

Acknowledgments. The authors would like to thank Leontine Alkema, Vladimíra Kantorová, Peiran Liu, Ema Perković, Hana Ševčíková, Nathan Welch, and Mark Wheldon for their helpful discussion and methodological support. We also thank the referees, Associate Editor, and Editor for their helpful comments.

Funding. This work was supported by NICHD grant R01 HD070936.

SUPPLEMENTARY MATERIAL

Supplementary material (DOI: 10.1214/23-AOAS1793SUPP; .pdf). Details for the full model specification, creation of SDG intervention projections of covariates, MCMC diagnostics, additional validation exercises, additional projection results, and additional comparisons with related work are provided in the supplementary material.

REFERENCES

ABEL, G. J., BARAKAT, B., KC, S. and LUTZ, W. (2016). Meeting the sustainable development goals leads to lower world population growth. *Proc. Natl. Acad. Sci. USA* **113** 14294–14299. https://doi.org/10.1073/pnas.1611386113

ADSERÁ, A. (2017a). Education and fertility in the context of rising inequality. *Vienna Yearb. Popul. Res.* **15** 63–92. https://doi.org/10.1553/populationyearbook2017s063

ADSERÁ, A. (2017b). The future fertility of highly educated women: The role of educational composition shifts and labor market barriers. *Vienna Yearb. Popul. Res.* **15** 19–25. https://doi.org/10.1553/populationyearbook2017s019

ALKEMA, L. (2020). The Global Burden of Disease fertility forecasts: Summary of the approach used and associated statistical concerns. OSF preprints. https://doi.org/10.31219/osf.io/3m6va

ALKEMA, L., RAFTERY, A. E., GERLAND, P., CLARK, S. J., PELLETIER, F., BUETTNER, T. and HEILIG, G. K. (2011). Probabilistic projections of the total fertility rate for all countries. *Demography* **48** 815–839. https://doi.org/10.1007/s13524-011-0040-5

AXINN, W. G. and BARBER, J. S. (2001). Mass education and fertility transition. *Am. Sociol. Rev.* **66** 481–505. https://doi.org/10.2307/3088919

AZOSE, J. J. and RAFTERY, A. E. (2015). Bayesian probabilistic projection of international migration rates. *Demography* **52** 1627–1650. https://doi.org/10.1007/s13524-015-0415-0

BONGAARTS, J. (1978). A framework for analyzing the proximate determinants of fertility. *Popul. Dev. Rev.* **4** 105–132. https://doi.org/10.2307/1972149

BONGAARTS, J. (1987). The proximate determinants of exceptionally high fertility. *Popul. Dev. Rev.* **13** 133–139. https://doi.org/10.2307/1972125

BONGAARTS, J. (2003). Completing the fertility transition in the developing world: The role of educational differences and fertility preferences. *Popul. Stud.* **57** 321–335. https://doi.org/10.1080/0032472032000137835

BONGAARTS, J. (2010). The causes of educational differences in fertility in sub-Saharan Africa. Poverty, gender, and youth. Working Paper no. 20. New York: Population Council. https://doi.org/10.31899/pgy3.1023

BONGAARTS, J. (2013). Demographic trends and implications for development. In *IUSSP* 2013 *Meeting*, *Busan*. Available at https://iussp.org/en/busan-conference-report.

BONGAARTS, J. (2016). Development: Slow down population growth. *Nature* **530** 409–412. https://doi.org/10.1038/530409a

BONGAARTS, J. (2017). The effect of contraception on fertility: Is sub-Saharan Africa different? *Demogr. Res.* **37** 129–146. https://doi.org/10.4054/DemRes.2017.37.6

BONGAARTS, J. and CASTERLINE, J. (2013). Fertility transition: Is sub-Saharan Africa different? *Popul. Dev. Rev.* **38** 153–168. https://doi.org/10.1111/j.1728-4457.2013.00557.x

BONGAARTS, J., FRANK, O. and LESTHAEGHE, R. (1984). The proximate determinants of fertility in sub-Saharan Africa. *Popul. Dev. Rev.* **10** 511–537. https://doi.org/10.2307/1973518

BONGAARTS, J., MENSCH, B. S. and BLANC, A. K. (2017). Trends in the age at reproductive transitions in the developing world: The role of education. *Popul. Stud.* **71** 139–154. https://doi.org/10.1080/00324728.2017.1291986

CAHILL, N., WEINBERGER, M. and ALKEMA, L. (2020). What increase in modern contraceptive use is needed in FP2020 countries to reach 75% demand satisfied by 2030? An assessment using the accelerated transition method and family planning estimation model. *Gates Open Res.* **4**. https://doi.org/10.12688/gatesopenres.13125.1

CALDWELL, J. C. (1982). *Theory of Fertility Decline*. Academic Press, New York.

CALDWELL, J. C., REDDY, P. H. and CALDWELL, P. (1985). Educational transition in rural south India. *Popul. Dev. Rev.* **11** 29–51. https://doi.org/10.2307/1973377

DE SILVA, T. and TENREYRO, S. (2017). Population control policies and fertility convergence. *J. Econ. Perspect.* **31** 205–228. https://doi.org/10.1257/jep.31.4.205

EASTERLIN, R. A. and CRIMMINS, E. M. (1985). *The Fertility Revolution*: *A Supply-Demand Analysis*. Univ. Chicago Press, Chicago, IL.

FABIC, M. S., CHOI, Y., BONGAARTS, J., DARROCH, J. E., ROSS, J. A., STOVER, J., TSUI, A. O., UPADHYAY, J. and STARBIRD, E. (2015). Meeting demand for family planning within a generation: The post-2015 agenda. *Lancet* **385** 1928–1931. https://doi.org/10.1016/S0140-6736(14)61055-2

FOSDICK, B. K. and RAFTERY, A. E. (2014). Regional probabilistic fertility forecasting by modeling between-country correlations. *Demogr. Res.* **30** 1011–1034. https://doi.org/10.4054/DemRes.2014.30.35

FRIEDMAN, J., YORK, H., GRAETZ, N., WOYCZYNSKI, L., WHISNANT, J., HAY, S. I. and GAKIDOU, E. (2020). Measuring and forecasting progress towards the education-related SDG targets. *Nature* **580** 636–639. https://doi.org/10.1038/s41586-020-2198-8

GIETEL-BASTEN, S. and SOBOTKA, T. (2020). Uncertain population futures: Critical reflections on the IHME scenarios of future fertility, mortality, migration and population trends from 2017 to 2100. SocArXiv. https://doi.org/10.31235/osf.io/5syef

GIETEL-BASTEN, S. and SOBOTKA, T. (2021). Trends in population health and demography. *Lancet* **398** 580–581. https://doi.org/10.1016/S0140-6736(21)01051-5

GODWIN, J. and RAFTERY, A. E. (2017). Bayesian projection of life expectancy accounting for the HIV/AIDS epidemic. *Demogr. Res.* **37** 1549–1610. https://doi.org/10.4054/DemRes.2017.37.48

GRANT, M. J. (2015). The demographic promise of expanded female education: Trends in the age at first birth in Malawi. *Popul. Dev. Rev.* **41** 409–438. https://doi.org/10.1111/j.1728-4457.2015.00066.x

HERZER, D., STRULIK, H. and VOLLMER, S. (2012). The long-run determinants of fertility: One century of demographic change 1900–1999. *J. Econ. Growth* **17** 357–385. https://doi.org/10.1007/s10887-012-9085-6

HIRSCHMAN, C. (1994). Why fertility changes. *Annu. Rev. Sociol.* **20** 203–233. https://doi.org/10.1146/annurev.so.20.080194.001223

KANEDA, T., FALK, M. and PATIERNO, K. (2021). Understanding and comparing population projections in sub-Saharan Africa. Available at https://www.prb.org/resources/understanding-and-comparing-population-projections-in-sub-saharan-africa/. Accessed: 2021-07-23.

KANTOROVÁ, V., WHELDON, M. C., UEFFING, P. and DASGUPTA, A. N. Z. (2020). Estimating progress towards meeting women's contraceptive needs in 185 countries: A Bayesian hierarchical modelling study. *PLoS Med.* **17** e1003026. https://doi.org/10.1371/journal.pmed.1003026

LEE, R. and MASON, A. (2006). What is the demographic dividend? *Financ. Dev.* **43** 16–24.

LIU, D. H. and RAFTERY, A. E. (2020). How do education and family planning accelerate fertility decline? *Popul. Dev. Rev.* **46** 409–441. https://doi.org/10.1111/padr.12347

LIU, D. H. and RAFTERY, A. E. (2024). Supplement to "Bayesian projections of total fertility rate conditional on the United Nations sustainable development goals." https://doi.org/10.1214/23-AOAS1793SUPP

LIU, P., ŠEVČÍKOVÁ, H. and RAFTERY, A. E. (2023). Probabilistic estimation and projection of the annual total fertility rate accounting for past uncertainty: A major update of the bayesTFR R package. *J. Stat. Softw.* **106** 1–36. https://doi.org/10.18637/jss.v106.i08

LUTZ, W. (2023). Population decline will likely become a global trend and benefit long-term human wellbeing. *Vienna Yearb. Popul. Res.* **21**. https://doi.org/10.1553/p-3cp7-4e6b

LUTZ, W., BUTZ, W. P. and KC, S., eds. (2014). *World Population and Human Capital in the Twenty-First Century* Oxford Univ. Press, Oxford.

LUTZ, W., GOUJON, A., KC, S., STONAWSKI, M. and STILIANAKIS, N., eds. (2018). *Demographic and Human Capital Scenarios for the* 21*st Century*: 2018 *Assessment for* 201 *Countries* Publications Office of the European Union, Luxembourg.

MAATHUIS, M. H. and COLOMBO, D. (2015). A generalized back-door criterion. *Ann. Statist.* **43** 1060–1088. MR3346697 https://doi.org/10.1214/14-AOS1295

MADDISON PROJECT DATABASE, VERSION 2018, BOLT, J., INKLAAR, R., DE JONG, H. and VAN ZANDEN, J. L. (2018). Rebasing 'Maddison': New income comparisons and the shape of long-run economic development. Maddison Project Working paper 10.

MARTÍN, T. C. (1995). Women's education and fertility: Results from 26 Demographic and Health Surveys. *Stud. Fam. Plan.* **26** 187–202. https://doi.org/10.2307/2137845

MASON, A. and LEE, R. (2006). Reform and support systems for the elderly in developing countries: Capturing the second demographic dividend. *Genus* **62** 11–35.

O'NEILL, B. C., DALTON, M., FUCHS, R., JIANG, L. and PACHAURI, S. (2010). Global demographic trends and future carbon emissions. *Proc. Natl. Acad. Sci.* **107** 17521–17526. https://doi.org/10.1073/pnas.10045811

PEARL, J. (1993). Comment: Graphical models, causality and intervention. *Statist. Sci.* **8** 266–269. https://doi.org/10.1214/ss/1177010894

PRESTON, S. H., HEUVELINE, P. and GUILLOT, M., eds. (2001). *Demography*: *Measuring and Modeling Population Processes* Blackwell Publishers, Oxford.

RAFTERY, A. E., ALKEMA, L. and GERLAND, P. (2014). Bayesian population projections for the United Nations. *Statist. Sci.* **29** 58–68. MR3201847 https://doi.org/10.1214/13-STS419

RAFTERY, A. E., ZIMMER, A., FRIERSON, D. M. W., STARTZ, R. and LIU, P. (2017). Less than 2 C warming by 2100 unlikely. *Nat. Clim. Change* **7** 637–641. https://doi.org/10.1038/nclimate3352

ŠEVČÍKOVÁ, H., ALKEMA, L. and RAFTERY, A. E. (2011). bayesTFR: An R package for probabilistic projections of the total fertility rate. *J. Stat. Softw.* **43** 1–29. https://doi.org/10.18637/jss.v043.i01

ŠEVČÍKOVÁ, H. and RAFTERY, A. E. (2016). bayesPop: Probabilistic population projections. *J. Stat. Softw.* **75** 1–29. https://doi.org/10.18637/jss.v075.i05

SOBOTKA, T., BEAUJOUAN, É. and VAN BAVEL, J. (2017). Introduction: Education and fertility in low-fertility settings. *Vienna Yearb. Popul. Res.* **15** 1–16. https://doi.org/10.1553/populationyearbook2017s001

SPERINGER, M., GOUJON, A., KC, S., POTANČOKOVÁ, M., REITER, C., JURASSZOVICH, S. and EDER, J. (2019). Global reconstruction of educational attainment, 1950 to 2015: Methodology and assessment. Vienna Institute of Demography. Working Papers No. 02/2019. https://doi.org/10.1553/0x003cb434

UNITED NATIONS, DEPARTMENT OF ECONOMIC AND SOCIAL AFFAIRS, POPULATION DIVISION (2019a). World population prospects: The 2019 revision. Online edition.

UNITED NATIONS, DEPARTMENT OF ECONOMIC AND SOCIAL AFFAIRS, POPULATION DIVISION (2019b). World population prospects 2019: Methodology of the United Nations population estimates and projections.

UNITED NATIONS (2015). Transforming our world: The 2030 agenda for sustainable development. Available at https://sdgs.un.org/2030agenda.

VOLLSET, S. E., GOREN, E., YUAN, C.-W., CAO, J., SMITH, A. E., HSIAO, T., BISIGNANO, C., AZHAR, G. S., CASTRO, E. et al. (2020). Fertility, mortality, migration, and population scenarios for 195 countries and territories from 2017 to 2100: A forecasting analysis for the Global Burden of Disease study. *Lancet* **396** 1285–1306. https://doi.org/10.1016/S0140-6736(20)30677-2

WILMOTH, J. (2019). Global population projections: A critical comparison of key methods and assumptions. Available at https://www.un.org/en/development/desa/population/about/director/pdf/Wilmoth_APC_Nov2019_Script.pdf.

WITTGENSTEIN CENTRE FOR DEMOGRAPHY AND GLOBAL HUMAN CAPITAL (2018). Wittgenstein Centre data explorer version 2.0. Available at http://www.wittgensteincentre.org/dataexplorer.