

Assessing the Impact of Potential Policies on Fertility in High-Fertility Countries using Granger Causality and Bayesian Hierarchical Models

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Abstract

The United Nations uses a Bayesian hierarchical model to create probabilistic projections of fertility. Women’s education and family planning (WEFP) are two mechanisms identified as having a potentially causal effect on fertility decline. Simultaneously, WEFP can be directly impacted by public policy initiatives. We assess the causal nature of WEFP on fertility decline using a Granger causality framework and propose a conditional Bayesian hierarchical model for fertility projections that conditions on the impact of different WEFP policies on fertility decline. By considering potential policy outcomes within population projection models, we can improve fertility projections and provide an informative tool for policymakers in high-fertility countries.

Introduction: The United Nations projects that world population will increase from its present 7.4 billion to 11.4 billion people in 2100, with about three-quarters of this increase in Sub-Saharan Africa, mostly in high-fertility countries (United Nations, 2017). Much of the rest of the increase will be in countries in Asia and Latin America with above-replacement fertility.

It is widely thought that these countries would benefit from a slower population increase brought about by a more rapid decrease in fertility (Bongaarts, 2013), as high fertility and rapid population growth are likely to have adverse economic, environmental, health, governmental, and political consequences. Also, declining fertility can yield a demographic dividend by reducing the dependence ratio, increasing women’s participation in the paid labor force, and allowing increased investments in human and physical capital (Lee & Mason, 2006; Mason & Lee, 2006).

This raises the question of how the fertility decline could be accelerated. There is widespread agreement in the literature that there are two main kinds of policy that can help achieve this: increasing women’s education and increasing family planning access and contraceptive prevalence (Hirschman, 1994). Here we address the question of what the likely quantitative demographic effect of such policies would be.

Methods: The U.N. projects the future Total Fertility Rate (TFR) in all countries using a Bayesian hierarchical model, and we build on this in our work. We focus here on the causal effect of women’s education and family planning, but for ease of explanation we couch our exposition in terms of women’s education. We assess the causal nature of women’s education on fertility decline using a Granger causality framework and propose a conditional Bayesian hierarchical model for projections of TFR that conditions on the impact of different education policies on fertility decline. The proposed model builds upon the unconditional model for probabilistic fertility projections currently used by the U.N. (Alkema et al., 2011; Raftery et al., 2014; Fosdick & Raftery, 2014). By developing methods for conditional probabilistic population projections given particular education policy options, we can improve fertility projections and provide an informative tool for policymakers in high-fertility countries.

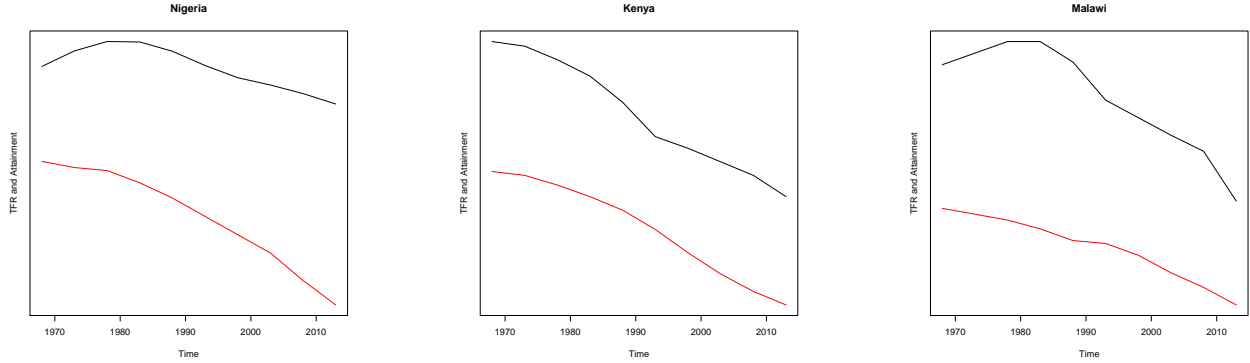


Figure 1: TFR (black line) and the proportion of women who did not attain at least Lower Secondary education (red line) for Nigeria, Kenya, and Malawi from 1965 to 2015

To estimate our models, we use U.N. data on past TFR for all countries (United Nations, 2017). We denote the TFR for country c at time period t as $\text{TFR}_{c,t}$. Five-year decrements in TFR are constructed as a measure of fertility decline, with TFR decrement defined as $\text{TFR}_{c,t} - \text{TFR}_{c,t+1}$. The expected TFR decrement for each country and time period is modeled using a double logistic function developed by Alkema et al. (2011).

We consider both educational attainment of women and enrollment rates of children. Educational attainment data for women are obtained from the Wittgenstein Centre (Lutz et al., 2014). Net Enrollment Rates for primary and secondary education are obtained from the World Bank. We consider both the original education covariates and their corresponding decrements. Finally, we identify a “high-fertility” subset of our data to serve as the main focus of our analyses. For each country, we are primarily interested in data corresponding to time periods where the country had TFR greater than 2.5.

Looking at TFR plotted alongside the proportion of women who did not attain at least Lower Secondary education for selected countries in Figure 1, we see the two are highly correlated. We evaluate whether this correlation results from a causal relationship between women’s education and fertility decline using a Granger causality framework. A variable X is said to “Granger-cause” variable Y if past observations of X provide us with additional information for forecasting Y that is not already captured in past or current values of Y (Hamilton, 1994). We treat women’s education as X and TFR decrement as Y . We use the expected TFR decrement in lieu of past values of TFR decrement.

The null hypothesis of our Granger causality test is that women’s education does not Granger-cause TFR decrement. For our preliminary results, this test is formulated as a likelihood ratio test. Let “Decr” denote a decrement term. Our test is then of the following nested models:

$$\mathbf{Full\ Model:} \text{TFR Decr}_{c,t} = \beta_0^{full} + \beta_1^{full}(\text{Expected Decr})_{c,t} + \alpha(\text{Education})_{c,t-1} + \varepsilon_{c,t} \quad (1)$$

$$\mathbf{Reduced\ Model:} \text{TFR Decr}_{c,t} = \beta_0^{red} + \beta_1^{red}(\text{Expected Decr})_{c,t} + \varepsilon_{c,t} \quad (2)$$

Here, c denotes one of 160 countries and t represents one of eight differences of 5-year time periods. To account for between-country correlation, we use generalized least squares (GLS) to fit our models via maximum likelihood. We assume correlated, homoscedastic, multivariate normal errors within each cluster and between-cluster independence.

Our choice of clustering scheme and correlation structure draws from Fosdick & Raftery (2014) and is based on U.N. region membership. As each U.N. region consists of countries that are both spatially contiguous and relatively culturally homogenous, we expect there to be similar between-country correlation for all countries in the same region and at the same time point. Thus, we construct

clusters for each U.N. region and time point pair and assume exchangeable within-cluster correlation.

To select our education covariates, we use Bayesian model selection with BIC as our model selection criterion (Raftery, 1995), where the model with the smallest BIC is preferred. This led us to select the decrement version of proportion of women who attained lower secondary education or higher (denoted “LowSec+ Decr”) and the proportion of women who attained incomplete primary education or higher (denoted “IncPri+”) as our education covariates. The full model including the expected decrement term, LowSec+ Decr, and IncPri+ had $R^2 = 0.372$. In comparison, the reduced model including only the expected decrement term had $R^2 = 0.304$.

Results: For our Granger causality test, we fit the full and reduced models in Equations (1) and (2) using GLS. The “Education” term in the full model consists of two covariates, LowSec+ Decr and IncPri+, both of which are lagged by one time point. The models are summarized below in Tables 1 and 2. The estimated within-cluster correlation is 0.24 in the full model and 0.28 in the reduced model.

| | Estimate | Standard Error | t Test Statistic | P-value |
|-----------------------|----------|----------------|------------------|----------|
| Intercept | -0.026 | 0.037 | -0.71 | 0.4752 |
| Exp Decr | 0.822 | 0.047 | 17.67 | < 0.0001 |
| LowSec+ Decr (Lagged) | -1.227 | 0.304 | -4.03 | 0.0001 |
| IncPri+ ($t - 1$) | 0.108 | 0.041 | 2.61 | 0.0093 |

Table 1: GLS fit for full model with selected education covariates, fit using R package `nlme`

| | Estimate | Standard Error | t Test Statistic | P-value |
|-----------|----------|----------------|------------------|----------|
| Intercept | 0.120 | 0.022 | 5.37 | < 0.0001 |
| Exp Decr | 0.803 | 0.046 | 17.42 | < 0.0001 |

Table 2: GLS fit for reduced model with selected education covariates, fit using R package `nlme`

Our Granger causality test (likelihood ratio test) is summarized in Table 3. We found our selected combination of education covariates resulted in sufficient evidence to reject the null hypothesis that LowSec+ Decr and IncPri+ do not Granger-cause TFR decrement.

| Model | DF | BIC | Log-likelihood | LR | P-value |
|---------|----|-------|----------------|-------|----------|
| Full | 6 | -0.68 | 20.20 | | |
| Reduced | 4 | 20.66 | 2.91 | 34.58 | < 0.0001 |

Table 3: Granger causality test (multivariate likelihood ratio test) for selected education covariates

From these preliminary results, we see that BIC selects the full model that includes education covariates over the reduced model. Our results also indicate we have sufficient evidence to reject the null hypothesis of no Granger causality between our selected education covariates and TFR decrement. These results suggest our education covariates provide additional information that is useful for predicting TFR decrement and that is not already captured by the expected decrement term. We expect these results to hold even after including measures of infant mortality and GDP as additional control variables in our full and reduced models.

Discussion: To assess the demographic implications of possible education policies, we will first incorporate the selected education variables into the existing Bayesian hierarchical model for TFR.

This will be done using a methodology similar to that of Godwin & Raftery (2017) for extending probabilistic projections of life expectancy to account for the HIV/AIDS epidemic. To do so, we will need to project our chosen education covariates into the future and incorporate education projection uncertainty into our projections of TFR. We will draw upon projection methods developed by Lutz et al. (2014). We will also assess the potential demographic of different future family planning policies by extending the model to include measures of family planning provision and contraceptive prevalence.

We expect that incorporating these education and family planning covariates into a new, conditional Bayesian hierarchical model for TFR will allow us to produce conditional probabilistic population projections given particular future educational participation trajectories. These should in turn give us an understanding of the possible demographic payoffs to given educational and family planning policies.

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References

- Alkema, L., Raftery, A. E., Gerland, P., Clark, S. J., Pelletier, F., Buettner, T., & Heilig, G. K. (2011). Probabilistic projections of the Total Fertility Rate for all countries. *Demography*, *48*(3), 815–839.
- Bongaarts, J. (2013). Demographic trends and implications for development. IUSSP 2013 Meeting, Busan.
- Fosdick, B. K. & Raftery, A. E. (2014). Regional probabilistic fertility forecasting by modeling between-country correlations. *Demographic Research*, *30*, 1011–1034.
- Godwin, J. & Raftery, A. (2017). Bayesian projection of life expectancy accounting for the HIV/AIDS epidemic. *Demographic Research*, *37*, 1549–1610.
- Hamilton, J. (1994). *Time series analysis*. Princeton University Press.
- Hirschman, C. (1994). Why fertility changes. *Annual Review of Sociology*, *20*, 203–233.
- Lee, R. & Mason, A. (2006). What is the demographic dividend? *Finance and Development*, *43*(3), 16–24.
- Lutz, W., Butz, W. P., , & Samir, K. (2014). *World Population and Human Capital in the Twenty-First Century*. Oxford University Press.
- Mason, A. & Lee, R. (2006). Reform and support systems for the elderly in developing countries: capturing the second demographic dividend. *Genus*, 11–35.
- Raftery, A. E. (1995). Bayesian model selection in social research (with discussion). *Sociological Methodology*, *25*, 111–196.
- Raftery, A. E., Alkema, L., & Gerland, P. (2014). Bayesian population projections for the United Nations. *Statistical Science*, *29*(1), 58–68.
- United Nations (2017). *World Population Prospects: The 2017 Revision*. New York, NY, USA: United Nations, Department of Economic and Social Affairs, Population Division.