Journal of Statistics ***ISSN-P: 1684-8403***
Volume 27, 2023, pp. 1-12 ***ISSN-E: 2957-8981***

Socioeconomic Determinants of Fertility Rate in Somalia

Liban Ali Mohamud[1]

Abstract

The primary objective of this research was to examine how socioeconomic variables affected the fertility rate in Somalia between 1990 and 2020. To accomplish this goal, the study was conducted by applying a vector error correction model to gauge the associations among socioeconomic factors and fertility rate. The study employed annual time series data obtained from the World Bank and the Statistical, Economic, and Social Research and Training Centre for Islamic Countries. The research discovered the long-term impact on the fertility rate due to various socioeconomic factors. Female labour force participation and GDP per capita participation rate were found to have a long-term, significant negative impact on Somalia's fertility rate, whereas the fertility rate was significantly and positively impacted over time by the infant mortality rate. The study also found that the fertility rate in Somalia was not significantly affected in the short run by socioeconomic factors. As a result, the study concludes that socioeconomic factors only have a long-term effect on the fertility rates in Somalia. The study suggests that based on its findings that the Somali Democratic Republic's government implement national policies aimed at promoting female empowerment in the workforce and education, which would directly reduce the fertility rate.

Keywords

TFR, GDP per capital, Johansen method, VECM Model and Wald test.

1. Introduction

Over the past few decades, a significant reduction in fertility rates in most countries worldwide has been found. According to the United Nations (2022a), about 67% global population living in the areas of fertility less than 2.1 children per woman. Currently, developed industrialized nations have a birth rate per woman below the replacement level, as noted by Aitken (2022). The declining trend of fertility rates is found in developing countries, with the total fertility rate dropped from seven births per woman in the 1950s to less than three births per woman in 2020, according to Bongaarts and Houghton (2022a). Meanwhile, Africa has experienced an unpredictable decline in fertility rates. Overall, fertility rates in Africa have dropped from over six births per female in the 1950s to less than five births per female in 2020.

According to Bongaarts and Hodgson (2022b), fertility rates have declined in the Eastern (7 to 4.4), Northern (6.8 to 3.3), Western (6.4 to 5.2), Southern (6.1 to 2.5), and Central/Middle (5.8 to 5.5) regions. However, it is worth noting that sub-Saharan Africa

---

[1]Department of Statistics and Planning, Faculty of Economics, SIMAD University, Mogadishu, Somalia.
Email: liban@simad.edu.so

(SSA) still has the highest fertility rates among the top three most populated regions globally, including Central and Southern Asia (28%), and Eastern and Southeastern Asia (18%), as per the United Nations (2022b).

The overall total fertility rate (TFR) for Somali women is 6.9 as found in 2020 in the Somali Demographic and Health Survey (SDHS). The highest TFR was observed among women residing in nomadic areas (7.3), followed by those in rural areas (7.1), and the lowest TFR was among women living in urban areas (6.4). These rates are more extreme than the TFRs found in the Sub-Saharan Africa (SSA) and the rest of the world, which are 4.6 and 2.5, respectively. The high TFR in Somalia contribute significantly to the high MMR (maternal mortality ratio) among Somali women (692 per 100,000), much higher than the rates in SSA (84.5 per 100,000) (Gele et al., 2022).

The total fertility rate is an essential health indicator that is linked to the infant mortality rate and population growth. Lowering the fertility rate is crucial for stabilizing the infant mortality rate and population growth in every country. As a result, the total fertility rate is a vital topic of discussion among policymakers, demographers, and researchers. Although the total fertility rate is a significant health indicator in Somalia, there is a lack of studies addressing this issue. The study focuses to determine the influence of socioeconomic factors on the fertility rate in Somalia from 1990 to 2020. The literature on fertility rate is categorized into two types: those that examine the determinants of fertility and those that investigate the consequences of fertility. This study falls under the category of the determinants of fertility in the context of Somalia.

The total fertility rate (TFR) defines as the average children born to a female (Yusuf et al., 2014). Previous literature has examined the impact of various socioeconomic factors on fertility rates and presented divergent views. For example, Fong (1978) found that female labor force participation and economic status were the most significant factors in reducing fertility in Malaysia. Poston and Zhongke (1990) conducted a study on the socioeconomic structure and fertility in China, revealing that infant mortality had a significant as well as positive effect on China's rate of fertility, while the urbanization rate and standard of living were negatively related to fertility. Miah and Mizan (1992) also discovered that the female labor force participation rate negatively affected the fertility rate. Muhidin et al. (2008) argued that the urbanization rate was negatively related to the fertility rate. Yurtseven (2015) noted that economic development was indirectly related to the fertility rate, as the latter decreased with a country's development. According to Khan (2017), the fertility rate also has a positive effect of urbanization rate on it, whereas women's education level was negatively linked to the fertility rate in both the short and long terms. Lastly, Qasim et al. (2016) stated that female literacy and GDP (gross domestic product) per capita had a significant and negative association with fertility rate, while child mortality was positively associated with it.

Numerous studies have been conducted worldwide to model the determinants of fertility rates. However, only a few studies have explored the issue of fertility in the context of Somalia. These studies include Aden et al. (2019), Gele et al. (2019), Gure, et al. (2015), Johnson and Elmi (1989), Omar, et al. (1994), Susuman et al. (2016). Although these studies are informative, they relied on simple descriptive statistics and classical regression models, which are unable to measure the short- and long-term effects of socioeconomic factors on the fertility rate in Somalia. In this study, a vector error correction model was used to analyze the long- and short-term effects of selected socioeconomic factors (namely, GDP per capita, urbanization rate, female labour force participation rate, and infant mortality rate) on the fertility rate in Somalia.

Using the vector error correction model (VECM) approach, the primary goal of this study is to ascertain if the chosen socioeconomic factors have both long- and short-term effects on the fertility rate in Somalia. The essay is set up like follows: The methodology and data are presented in Section 2, followed by the findings in Section 3, then the conclusion and recommendations in Section 4.

2. Methods and data

2.1 Data description

This study investigates the influence of socioeconomic factors on the fertility rate in Somalia from 1990 to 2020. The data used in the analysis were obtained from the World Bank and the Statistical, Economic, and Social Research and Training Centre for Islamic Countries, and consist of annual time series data. Table 1 provides information about the variables, measurements, and data sources used in the study. The dependent variable is the total fertility rate, which is determined by calculating the average number of births per woman between the ages of 15-49. The independent variables used in the study include GDP per capita, female labor force participation rate, infant mortality rate, and urbanization rate. The GDP per capita is measured in USD, and the infant mortality rate is measured by the number of deaths per 1,000 births. Urbanization is calculated as the proportion of the population residing in urban in the total population, while the female labor force participation rate is determined by the proportion of women in the entire workforce.

Table 1: Variables, measurement, and data sources.

Variables	Measurements	Data Sources
Total fertility rate (TFR)	Measured Births per woman	WBDI 1990-2020
GDP per capital (GDPP)	measured USD	SESRIC DATA 1990-2020
Urbanization (UP)	measured as the proportion of the population residing in urban	SESRIC DATA 1990-2020
Female Labor Force Participation rate (FLP)	Measured the percentage of female in total labour force	WBDI 1990-2020
Infant Mortality rate (IMR)	Measured deaths per 10000 births	SESRIC DATA 1990-2020

2.2 Statististical method

2.2.1 Vector Error Correction Model

The Vector Error Correction Model (VECM) was initially introduced to economics by Sargan, a British econometrician, in 1964. It proves to be a valuable tool when analyzing non-stationary time series data that display a cointegration relationship between variables. The VECM model allows the estimation of both short-term and long-term effects between variables, making it a suitable choice for econometric analysis of non-stationary but cointegrated time series (Montgomery, 2015). The general structure of the VECM model with Q-1 lags can be expressed as follows:

$$\Delta y_t = \beta_0 + \sum_{i=1}^{Q-1} \delta_i \Delta Y_{t-i} + \sum_{i=1}^{Q-1} \beta_i \Delta X_{t-i} + \phi(y_{t-1} - \beta_0 - \beta_1 x_{t-1}) + \mathcal{E}t \quad (1)$$

where, $\mathcal{E}t$ is the error term, $\sum_{i=1}^{Q-1} \delta_i \Delta Y_{t-i}$ is the lag of the response variable, $\sum_{i=1}^{Q-1} \beta_i \Delta X_{t-i}$ is the lag of the covariates, β_i are the short term coefficients of the explanatory variables, ϕ is the long run coefficient of the error correction term, Q-1 is the optimal lag number of both response variable and covariates and $\Delta$is the differencing operator. Equation (1) can be reduced by replacing this term $y_{t-1} - \beta_0 - \beta_1 x_{t-1}$ into Z_{t-1}

$$\Delta y_t = \beta_0 + \sum_{i=1}^{Q-1} \delta_i \Delta Y_{t-i} + \sum_{i=1}^{Q-1} \beta_i \Delta X_{t-i} + Z_{t-1} \quad (2)$$

The OLS residual from the cointegration long-run regression, which is denoted as (Z_{t-1}), is commonly known as the error correction term (ECT). This term is defined as follows.

$$y_t = \beta_0 - \beta_1 x_t \quad (3)$$

The above equation (3) shows the long run regression model.

$$ECT = Z_{t-1} = (y_{t-1} - \beta_0 - \beta_1 x_{t-1}) \quad (4)$$

The coefficient of ECT indicates the speed at which variable $y_t$reverts to its equilibrium state after a change in variable xt. A significant and negative coefficient (ϕ) suggests that all explanatory variables have a robust long run correlation with the response variable.

2.2.2 Model specification

In this study, the influence of socioeconomic factors on fertility rates in Somalia is examined using the Vector Error Correction Model. The study investigates the stochastic relationship between TFR and important variables such as GDPP, FLP, IMR, and UP. The VECM Model can be used to express this relationship in the following manner.

$$\Delta TFR_t = \beta_0 + \sum_{i=1}^{Q-1} \delta_i \Delta TFR_{t-i} + \sum_{i=1}^{Q-1} \beta_i \Delta GDPP_{t-i} + \sum_{i=1}^{Q-1} \beta_i \Delta IMR_{t-i} + \sum_{i=1}^{Q-1} \beta_i \Delta FLP_{t-i} + \sum_{i=1}^{Q-1} \beta_i \Delta UP_{t-i} + \emptyset Z_{t-1} + \mathcal{E}t \quad (5)$$

where,
ΔTFR_t= the total fertility rate at first difference.
ΔTFR_{t-i} =the total fertility rate at the first difference of Q-1 lags.
$\Delta GDPP_{t-i}$ =GDP per capital at the first difference of Q-1 lags.
ΔIMR_{t-i} = the infant mortality rate at the first difference of Q -1 lags
ΔFLP_{t-i} = female labor, forcing participation rate at the first difference of Q -1 lags.
ΔUP_{t-i} =the urbanization rate at the first difference of Q -1 lags.
$\mathcal{E}t$ = error term.

Z_{t-1} is the error correction term at time *"t-1"* and the coefficients "β_i" and "ϕ" correspond to the short-run and long-run components of the model, respectively.

2.3 Analysis of stationarity

To avoid spurious results in time series data, it is necessary to test for the presence of a unit root, as non-stationary data with changing mean and variance over time can lead to biased results when used at their level. Although such data may yield significant coefficients and a high R-square, the results may lack reliability. Therefore, it is crucial to determine the order of integration of each variable in the model to ascertain the presence of unit roots (Rudebusch, 1992). A standard statistical technique for detecting if a time series is stationary or not is the Augmented Dickey-Fuller test. The typical notation often used to represent the ADF test is as follows.

$$\Delta R_{t-1} = \varphi R_{t-1} + \sum_{i=1}^{Q-1} \theta_i \Delta R_{t-i} + \mu_{1t} \quad (6)$$

$$\Delta R_{t-1} = \alpha + \varphi R_{t-1} + \sum_{i=1}^{Q-1} \theta_i \Delta R_{t-i} + \mu_{2t} \quad (7)$$

$$\Delta R_{t-1} = \alpha + \beta t + \varphi R_{t-1} + \sum_{i=1}^{Q-1} \theta_i \Delta R_{t-i} + \mu_{3t} \quad (8)$$

$H_o: \varphi = 0$ (Have a unit root problem)
$H_o: \varphi < 0$ (Not possess a unit-root problem)

If the probability (t-statistics) of ADF test is less than 5%, then the series is free from the unit root problem, otherwise it has.

2.4 Johansen cointegration approach

The co-integration method was employed to assess if non-stationary variables exhibited long-term co-movement. This process for counting the number of Johansen cointegration equations between variables uses the max - eigen and the trace statistics, two widely used statistical methodologies (Kirchgässner et al., 2012a). The greatest Eigenvalue technique contrasts the option of k+1 cointegrating relations with the null hypothesis of b cointegrating relations for b = 0, 1, 2, ..., k-1. The following formula is used to calculate the Maximum-Eigenvalue strategy.

$$LR_{max}(b/k+1) = -n * \ln(1-\hat{\lambda}_{i+1}) \quad (9)$$

where, n represents the number of samples and λ is the highest Eigenvalue. In trace statistics, the study hypothesis of k cointegration relations, where k is the number of variables present in the system for b = 0, 1,2 k - 1, is compared to the positive claim of having cointegration relations. The trace statistics are computed using the following equation.

$$LR_{tr}(b/k) = -n * \sum_{i=b+1}^{k} \ln(1-\hat{\lambda}_i). \quad (10)$$

In the case of LR_{max} and LR_{tr} yield different result then the trace statistics result should prefer (Kirchgässner et al., 2012b).

3. Findings

3.1 Descriptive analysis

As shown in Table 2, UP has the highest average compared all other variables and is about 4077649, while TFR has the lowest average 7.07. As regards to the volatility of the variables the UP show the highest volatility 1641271% (as Measured by the standard deviation), whereas the TFR has the lowest volatility of 0.589 %. Regarding to higher moments, all variables skewed to the right of the normal curve except the TFR which is negatively skewed.

Table 2: Descriptive analysis.

	TFR	**UP**	**IMR**	**GDPP**	**FLP**
Mean	7.072	4077649	94.743	149.445	30.678
Median	7.310	3793358	93.481	136.202	30.540
Maximum	7.690	7333290	128.155	233.878	32.197
Minimum	5.890	2142817	65.664	79.948	29.749
Std. Dev.	0.589	1641271	19.442	49.735	0.771
Skewness	-0.663	0.510	0.310	0.516	0.437
Kurtosis	2.026	1.960	2.025	1.902	1.887
Observations	31	31	31	31	31

Note: IMR stands for infant mortality rate, TFR for total fertility rate, GDPP for GDP per capita, FLP for female labor force participation, and UP for urban population rate

3.2 Correlation analysis

Table 3 reveals that there is a strong negative relationship of TFR with UP. There is also a strong positive association of TFR with IMR. While there is a weak negative association of TFR with both GDPP and FLP. Moreover, the table also indicates that the TFR and UP has a high correlation coefficient of 0. 976. While TFR and FLP have the lowest correlation coefficient 0.019.

Table 3: Correlation analysis.

	TFR	**UP**	**IMR**	**GDPP**	**FLP**
TFR	1.000	-0.976	0.862	-0.482	-0.019
UP		1.000	-0.947	-0.371	-0.191
IMR			1.000	0.162	0.471
GDPP				1.000	-0.383
FLP					1.000

Note: IMR stands for infant mortality rate, TFR for total fertility rate, GDPP for GDP per capita, FLP for female labor force participation, and UP for urban population rate.

3.3 Unit root analysis

In order to avoid the issue of false results, it is imperative to do a unit root checks on historical data. The ADF test was used to investigate the unit root of the data, and the results are displayed in Table 4. Table 4 shows the results of the ADF unit root test and shows that all variables have unit issues at their level. Yet, at the first difference, all null hypotheses for the variables were rejected. Additionally, it demonstrates that at the first difference, all variables are stationary.

Table 4: Unit analysis (ADF Test).

At I(0) Intercept and Trend			**At I(1) Difference Intercept and Trend**		
Variables	t-statistics	Prob.	Variables	t-statistics	Prob.
TFR	-9.03	0.001	ΔTFR	-4.339	0.045
UP	-1.216	0.805	ΔUP	-5.232	0.001
IMR	1.434	0.813	ΔIMR	-4.504	0.008
FLP	-2.583	0.977	ΔFLP	-4.309	0.015
GDPP	-3.282	0.677	ΔGDPP	-4.664	0.004

Note: IMR stands for infant mortality rate, TFR for total fertility rate, GDPP for GDP per capita, FLP for female labor force participation, and UP for urban population rate.

3.4 Optimal lag length

The best lag size for the model must be selected in order to carry out the cointegration test. By choosing the lag length that results in the lowest criterion information, popular techniques like the Akaike Information Criterion (AIC), SC Schwarz-Bayesian, and HQ Hannan criteria can be used to establish the ideal lag length. To guarantee the correctness and dependability of the findings of the cointegration test, it is crucial to identify the ideal lag size. Lag 3 is the best because it has the lowest values of the criterion information, including AIC, SC, FPE, HQ, and LR, as illustrated by Table 5.

Table 5: Choosing optimal lag length.

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	-621.405	NA	1.86e+13	44.743	44.981	44.816
1	-358.223	413.571	785906.6	27.730	29.158	28.167
2	-272.669	103.886	12566.27	23.405	26.022	24.205
3	-183.841	76.139*	230.096*	18.846*	22.652*	20.009*

Note: AIC = Akaike information criterion, SC = Schwarz information criterion, and HQ = Hannan-Quinn information criterion. LR = sequential modified LR test statistic. The lag order chosen by the criterion is shown by the '*'.

3.5 Cointegration analysis

The second phase involves deciding if the possible combination of the variables is stationary after passing the unit root test and resolving the non-stationary problem using the first differencing on every variable. The Johansen method of cointegration was used to verify if each variable unit root were unique.

The findings of the cointegration test analysis are shown in Table 6, and they illustrate that there are four cointegration equations between the fertility rate in Somalia and a few socioeconomic factors, including GDPP, FLP, UP, and IMR. The trace statistics and Max-Eigen statistics, both of which exhibit values above the critical value at a 5% significant level. This shows that socioeconomic conditions and fertility rates have a sustained association. TFR, GDPP, IMR, UP, and FLP converge over time when cointegration is present. Even though there is a fluctuating disparity between them, it eventually converges. These results imply that socioeconomic variables have a long-term effect on the fertility rate in Somalia.

Table 6: Johansen cointegration analysis.

Hypothesized No. of CE(S) value	Trace statistics	5% critical value	Max-eigen statistics	5% critical value
$r = 0$	268.668	69.819	119.674	33.877
$r \leq 1$	148.995	47.856	77.507	27.584
$r \leq 2$	71.487	29.797	45.923	21.132
$r \leq 3$	25.565	15.495	24.784	14.264
$r \leq 4$	0.781	3.841	0.781	3.841

3.6 Normalized cointegrating coefficients

The cointegrating coefficients are normalized once the cointegration test analysis is completed in order to assess the model's parameters and their statistical significance. The values in the parenthesis represent the standard error. Dividing the coefficients by the standard error gives the t-statistics enclosed in square brackets.

Table 7: Normalized cointegrating coefficients.

TFR	UP	IMR	GDPP	FLP
1.0000	-5.09E-08	0.056	-0.004	-1.109
	(5.8E-07)	(0.006)	(0.003)	(0.094)
	[-0.088]	[8.669]	[-15.822]	[-11.784]

Note: IMR stands for infant mortality rate, TFR for total fertility rate, GDPP for GDP per capita, FLP for female labor force participation, and UP for urban population rate.

After normalizing the cointegrating coefficients, Table 7 shows that, after correcting for other factors, the UP has a non-significant negative effect on TFR. This implies that UP and TFR move in the opposite direction and have a negative connection over time. Although accounting for other factors, the GDPP, on the other hand, has a negative and statistically significant effect on TFR. This suggests that GDPP and TFR move in opposite directions over the long term and have a negative and significant association. Even accounting for other factors, the FLP similarly has a negative and substantial effect on TFR. This suggests that FLP and TFR move in opposite ways over the long term and have a negative and substantial association. Lastly, after adjusting for other factors, the IMR has a positive and substantial effect on TFR. This shows that over time, IMR and TFR have a positive and significant association and move in the same direction.

3.7 Vector Error Correction Model and Wald test

We chose to use the VECM rather than the VAR since the results of the cointegration analysis trace statistics and Max-Eigen statistics show a strong connection between the selected socio-economic determinants and fertility rate. The variables and the outcome variable have a long-term relationship if the VECM model's rate of adjustment towards long-term equilibrium (Z_{t-1}) is non-positive and substantial. However, we used the Wald test of short-run causality to look for any short-term links between the chosen socioeconomic characteristics and fertility rate.

Table 8: VECM model.

Dependent Variable: D (TFR)
Method: Least Squares (Gauss-Newton / Marquardt steps)

	Coefficient	Std. Error	t-Statistic	Prob.
Z_{t-1}	-0.133	0.035	-3.820	0.002
R-squared	0.993	Mean dependent var		-0.057
Adjusted R-squared	0.988	S.D. dependent var		0.051
S.E. of regression	0.007	Akaike info criterion		-7.224
Sum squared resid	0.001	Schwarz criterion		-6.653
Log likelihood	113.141	Hannan-Quinn criter.		-7.049
F-statistic	205.926	Durbin-Watson stat		2.158
Prob (F-statistic)	0.000			

Table 8 demonstrates that the outcomes of the VECM model suggest a long-term association between the variables (i.e., UP, IMR, FLP, GDPP, and TFR). This is because the model'sZ_{t-1} is substantial and non-positive. The goodness of fit of the VECM result is also evaluated using the R-square. It assesses how effectively predictor variables account for variations in the dependent variable. Nonetheless, the R square for this study is 99.3%, indicating that factors like per capita GDP, the percentage of women in the labour force, infant mortality, and urbanisation rates can explain 99.3% of the variation in the total fertility rate. While the remainder of the variation is explained by other determinant variables that were not included in the model but were included in the error term. The validity of the model is examined using R-square and DW statistics. The model is deemed to be valid if DW exceeds R-square; otherwise, it is not. The model is reliable because DW (2.158) exceeds R square (99.3%).

Table 9: Wald test of short run relationships.

Test Statistic	Value	DF	Probability
F-statistic	1.637	(8, 16)	0.191
Chi-square	13.096	8	0.108

In Table 9, the result of the Wald test reveals that the coefficient of IMR, GDPP, UP and FLP are statistically insignificant since probability of (Chi-square test/F-statistics) is more 5% significant level, meaning that the covariate variables don’t have short-run relationships with TFR.

3.8 Analysis of a model diagnostic tests

Table 10 shows that the residuals are regularly distributed since the Jarque-Bara test has a higher than 5% chance of being significant. The model is also free of autocorrelation problems since Breusch-Godfrey F statistics and observed R-squared are more likely to be greater than a 5% significant threshold. It is likely that the model has a constant variance if the Breusch-Pagan-Godfrey test reveals both positive F-statistics and an observed R-squared over a 5% significant threshold.

Table10: Heteroskedasticity, autocorrelation and normality tests.

Problem		Statistic	p-value
Heteroskedasticity			
	F	1.666	0.188
	R^2	18.919	0.217
Autocorrelation			
	F	0.607	0.558
	R^2	2.235	0.327
Normality			
	Jargue Bera test	0.073	0.964

4. Conclusion and recommendation

The central objective of this study was to investigate how socioeconomic factors may have an influence on Somalia's fertility rate between 1990 and 2020. To evaluate the effects of socioeconomic determinants on reproduction rates, this study used a VECM model. According to a Johansen Test of Co-integration and VEC model, the study concluded that socioeconomic factors had a long-term effect on the fertility rate. The study reveals that the IMR has positive and significant long-term effects on Somalia's fertility rate, whereas GDPP and FLP have negative and significant short-term effects.

The study also discovered that, as the Wald test indicates, socioeconomic characteristics in Somalia had no short-term impact on fertility rates. Consequently, the study's findings indicate that the socioeconomic determinants in Somalia's fertility rate only had a long-term influence.

The study's findings recommend the following policies:

i. The government of the Somali Democratic Republic should implement national policies aimed at promoting female employment to accommodate the increasing number of women entering the labor force, which can lead to an immediate reduction in fertility rates.
ii. To decrease fertility rates, the government of the Somali Democratic Republic should improve the standard of living of its citizens.
iii. The government of the Somali Democratic Republic should implement measures to enhance the health sector, particularly for children under five, which can contribute to a decrease in fertility rates.

Acknowledgements

I appreciate the support in planning and reading the entire paper provided by my research supervisor, Dr. Jamal Abdul Nasir, Associate Professor and Chair at the Department of Statistics, Faculty of Mathematical and Physical Sciences, Government College University Lahore, Pakistan.

References

1. Aden, J. A., Ahmed, H. J. and Ostergren, P. O. (2019). Causes and contributing factors of maternal mortality in Bosaso District of Somalia. A retrospective study

of 30 cases using a Verbal Autopsy approach. *Global health action*, 12(1), 1672314.doi: 10.1080/16549716.2019.1672314.

2. Aitken, R. J. (2022). The changing tide of human fertility. *Human Reproduction*, 37(4), 629-638.
3. Bongaarts, J., and Hodgson, D. (2022a). *The Developing World's Fertility Transition: 2000–2020. In Fertility Transition in the Developing World* (pp. 123-139). Springer, Cham.
4. Bongaarts, J., and Hodgson, D. (2022b). *The Developing World's Fertility Transition: 2000–2020. In Fertility Transition in the Developing World* (pp. 123-139). Springer, Cham.
5. Ericsson, N. R., and MacKinnon, J. G. (2002). Distributions of error correction tests for cointegration. *The Econometrics Journal*, 5(2), 285-318.
6. Fong, C. O. (1978). *Socio-economic determinants of fertility in peninsular Malaysia*. SEAPRAP research report; no. 19.
7. Gele, A. A., Musse, F. K., and Qureshi, S. (2019). Unmet needs for contraception: A comparative study among Somali immigrant women in Oslo and their original population in Mogadishu, Somalia. *PLOS ONE*, 14(8). doi.org/10.1371/journal.pone.0220783
8. Gele, A. A., Shrestha, M., Sheikh, N. S., and Qureshi, S. A. (2022). Pregnant and Powerless: Exploring Barriers to Contraceptive use among Women in Mogadishu, Somalia. *Health Services Research and Managerial Epidemiology*, 9(2), 23-40.
9. Gure, F., Yusuf, M., and Foster, A. M. (2015). Exploring Somali women's reproductive health knowledge and experiences: results from focus group discussions in Mogadishu. *Reproductive health matters*, 23(46), 136-144.
10. Johnson, N. E., and Elmi, A. M. (1989). Polygamy and fertility in Somalia. *Journal of Biosocial science*, 21(2), 127-134.
11. Khan, S. A. (2017). Macro-Economic Determinants of Fertility Rate: A case study of Pakistan. *Bulletin of Business and Economics (BBE)*, 6(4), 166-174.
12. Kirchgässner, G., Wolters, J., and Hassler, U. (2012a). *Introduction to Modern Time Series Analysis*. Springer Science & Business Media.
13. Kirchgässner, G., Wolters, J., and Hassler, U. (2012b). *Introduction to Modern Time Series Analysis*. Springer Science and Business Media.
14. Miah, M. M. R., andMizan, A. N. (1992). Labor force participation and fertility: A study of married women in Bangladesh. *International Journal of Sociology of the Family*, 22(2),69-82.
15. Montgomery, D. C., Jennings, C. L., and Kulahci, M. (2015). *Introduction to Time Series Analysis and Forecasting*. John Wiley & Sons.
16. Omar, M. M., Hogberg, U., and Bergström, B. (1994). Fertility, infertility, and child survival of Somali women. *Scandinavian Journal of Social Medicine*, 22(3), 194-200.
17. Poston, D., and Zhongke, J. (1990). Socioeconomic structure and fertility in China: A county level investigation. *Journal of Biosocial Science*, 22(4), 507-515.
18. Qasim, M., Pervaiz, Z., and Chaudhary, A. R. (2016). Socioeconomic determinants of fertility: a cross districts analysis of Punjab, Pakistan. *Pakistan Journal of Humanities and Social Sciences*, 4(2), 37-48.
19. Rudebusch, G. D. (1992). Trends and random walks in macroeconomic time series: A re-examination. *International Economic Review*, 661-680.

20. Somali National Bureau of Statistics. (2020). https://www.nbs.gov.so/home. https://somalia.unfpa.org/sites/default/files/pubpdf/FINAL%20SHDS%20Report%202020_V7_0.pdf
21. Susuman, A. S., Chialepeh, W. N., Bado, A., and Lailulo, Y. (2016). High infant mortality rate, high total fertility rate and very low female literacy in selected African countries. *Scandinavian Journal of Public Health*, 44(1), 2-5.
22. United Nations Department of Economic and Social Affairs, Population Division. (2022a). World Population Prospects 2022: Summary of Results.
23. United Nations Department of Economic and Social Affairs, Population Division. (2022b). World Population Prospects 2022: Summary of Results.
24. White, M. J., Muhidin, S., Andrzejewski, C., Tagoe, E., Knight, R.,z and Reed, H. (2008). Urbanization and fertility: An event-history analysis of coastal Ghana. *Demography*, 45(4), 803-816.
25. Yurtseven, C. (2015). The socioeconomic determinants of fertility rates in Muslim countries: A dynamic panel data analysis. *Economics and Sociology*, 8(4), 165.
26. Yusuf, F., Swanson, D. A., and Martins, J. M. (2014). *Methods of Demographic Analysis.*