THE DYNAMICS OF FEMALE LIFE EXPECTANCY AND TOTAL FERTILITY RATE IN BANGLADESH: A TIME-SERIES ANALYSIS

Zerin Jannat

[1)] *MSc. in Economics, Department of Economics – Stockholm University, SE 10691, Stockholm, Sweden*
** Corresponding author: e-mail: zerinjannat@gmail.com, zeja8045@student.su.se*
ORCID: https://orcid.org/0000-0001-5909-4468

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Abstract

The association between female life expectancy and total fertility rate (TFR) is seldom explored and little understood. This study empirically explores the nature and dynamics of the relationship between female life expectancy and total fertility rate. Secondary data over the period 1973-2019 have been used from Bangladesh and obtained from the World Bank Dataset. Data have been analyzed using the vector autoregressive (VAR) framework that includes methods of inferences such as the Granger causality test and impulse response analysis. The association between female life expectancy and total fertility rate is negative for Bangladesh. The negative impact of total fertility rate on female life expectancy is statistically significant and prominent. A one standard deviation shock to total fertility rate can lead to a persistent decline in female life expectancy. On the contrary, the impact of female life expectancy of total fertility rate is observed to be of little magnitude. Greater attention needs to be paid to total fertility rate given the substantial impact it exerts on female life expectancy. In Bangladesh, total fertility rate has become static in recent years and a decline in use of all family planning methods has also been observed during the COVID-19 pandemic. This decline could exert shock on the total fertility rate and thus, lead to a persistent decline in female life expectancy. The findings of this study recommend that pragmatic approaches, such as regular recruitment and training of field-level workers to counsel women on FP methods, be adopted to enhance recovery of FP methods use and cushion the total fertility rate as well as female life expectancy from any shocks caused by decline in use of FP methods during the COVID-19 pandemic.

Keywords: *Female life expectancy, total fertility rate, vector autoregressive (VAR) framework, Granger-causality test, impulse response function, Bangladesh*

Statement of the problem in general outlook and its connection with important scientific and practical tasks

Life expectancy at birth depicts the overall mortality level of a population and is one of the indicators of human development (1). Female life expectancy is defined as the number of years a female is expected to live and this increased globally during the period 1970-1990(2). Life expectancy is said to affect fertility rate and lower fertility is associated

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with greater empowerment of women(3,4). Globally, total fertility (TFR) fell from 4.5 births per woman in the period 1970-1975 to 2.5 births per woman in 2010-2015(5). Bangladesh is a lower- middle-income economy of South Asia where female life expectancy and TFR have undergone significant demographic changes since the country gained sovereignty in 1971. Life expectancy rose from 46.7 to 72.6 years from 1973-2019 and the rise in female life expectancy was from 45.9 to 74.6 years within the same time frame(6,7). The rise in female life expectancy is greater and has exceeded male life expectancy since the year 2000 in the country (1). The change in TFR, however, has been more prominent and dramatic. Within the time period 1975-2017, the average number of children born to each woman plummeted from 6.8 to 2.1. A stellar sevenfold rise in contraceptive prevalence rate (CPR) was also observed within the same period (8). The 'reproductive revolution' in Bangladesh is globally recognized but the country has one of the highest population densities and is one of the most populous nations in the world (9).

Analysis of latest research where the solution of the problem was initiated

Different studies have reported negative association between life expectancy and fertility. Kabir (2008) found that a 10% rise in TFR was followed by a 1.5% decline in life expectancy in developing nations (10). Authors Barlow and Vissandjée (1999) reported that a reduction of TFR from 6 to 3 births per woman led to an increase in life expectancy by 3.5 years in developing and developed nations (11). It has also been argued that life expectancy varies in accordance with level of development, an observation especially relevant for women. El-Ghannam (2005) found that higher female life expectancy along with greater participation of women in labor force exerted significant and negative impact on TFR. The impact was more pronounced for less developed countries compared to countries more developed(2) .

Aims of paper. **Methods**

There is a dearth of literature that explores the relationship between female life expectancy and TFR. This study attempts to fill that gap by empirically examining the mentioned relationship. It also aims to explore the dynamics and interaction(s) of the aforementioned time series variables, possible impact(s) of shock(s), and policy implications. To meet these purposes, data from Bangladesh during time period 1973-2019 and a vector autoregressive (VAR) model with optimal lag length have been employed in this study.

Data and Methods

Data for this study have been obtained from the World Development Indicators of the World Bank database. The data set is balanced and comprises annual observations from Bangladesh over the period 1973-2019. The two variables used are female life expectancy and total fertility rate and their mean values are 62.17 years and 4.04%, respectively.

Introduction to the vector autoregressive (VAR) model

The vector autoregressive (VAR) model is a basic econometric and powerful tool that has a wide range of applications(12).It can study interaction among economic variables and also be used for forecasting. A significant advantage of the model is that it can statistically represent the dynamic behavior of time series data but does not impose restrictions over

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the underlying economic structure (13). To develop a stable VAR model, the following steps need to be followed:

- Ensure stationarity of the time series data variables using a stationarity test
- Determine optimal lag length using model selection criteria
- Build the VAR model with the stationary data variables and optimal lag length and check stability of the model
- Assess residual correlation with Lagrange Multiplier (LM) test
- Perform the Granger Causality Test

Stationarity and lag length selection

A stationary time series has constant mean and variance over time. Furthermore, its covariance is only dependent on the lag (i.e. distance) between two time periods (14). Non-stationary data will cause the VAR model to become unstable and yield inaccurate statistics. Thus, the VAR model can only be applied to time series data that are stationary and to test stationarity of the data variables, I use the Augmented Dickey-Fuller (ADF) Test. Null hypothesis for the ADF test is presence of unit root, i.e. the variable is non-stationary. If the null hypothesis cannot be rejected, differencing is then required to transform each variable into its stationary form. I denote the stationary form of female life expectancy and TFR as LifeEx $(Y_{LifeEx,t})$and Fer$(Y_{Fer,t})$, respectively throughout rest of this study.

Once the stationary forms of the data variables are obtained, the next step is to select appropriate lag length to build and estimate a VAR model is. Lag length is defined as the number of past values of a time series variable that can be used to predict the VAR model (15). The lag length for the VAR model can be chosen through model selection criteria and as a general rule, an optimal lag length (p) is the one that minimizes some model selection criteria. Two most commonly used are Akaike Information Criterion (AIC) and Schwarz-Bayesian Information Criterion (SBIC):

$$AIC(p) = \ln|\bar{\sum}(p)| + \frac{2}{T}\, pn^2 \qquad (1.1)$$

and

$$SBIC(p) = \ln|\bar{\sum}(p)| + \frac{\ln T}{T}\, pn^2 \qquad (1.2)$$

where$\bar{\sum}(p) = T^{-1}\sum_{t=1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_t'$ and p, T, and n denote lag length, sample size, and number of variables. Once optimal lag length is found, the VAR model can then be estimated either through ordinary least square (OLS) method or maximum likelihood method(15).

Stability of the VAR model

A basic VAR model uses multivariate time series and each variable can be expressed as a linear function past lags of itself and of other variables. A VAR model with maximum lag of p can be denoted as VAR (p) and below a bivariate VAR (3) is shown in different forms using *Fer*$(Y_{Fer,t})$ and *LifeEx*$(Y_{LifeEx,t})$:

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Basic form:

$$Y_t = C + \tau_1 Y_{t-1} + \tau_2 Y_{t-2} + \tau_3 Y_{t-3} + \varepsilon_t \qquad (1.3)$$

Where,

$Y_t = \begin{bmatrix} Y_{Fer,t} \\ Y_{LifeEx,t} \end{bmatrix}$ which is a (2x1) vector of variables. The $\tau_1, \tau_2,$ and τ_3 represent a (2x2) vector of coefficients, and ε_t is a vector of error terms which is assumed to have zero mean, no autocorrelation and a covariance matrix that is time invariant. Time period is denoted by t and t= 1,2,……..T

In matrix form:

$$\begin{bmatrix} Y_{Fer,t} \\ Y_{LifeEx,t} \end{bmatrix} = \begin{bmatrix} c_{Fer} \\ c_{LifeEx} \end{bmatrix} + \begin{bmatrix} \tau^1_{1,1} & \tau^1_{1,2} \\ \tau^1_{2,1} & \tau^1_{2,2} \end{bmatrix} \begin{bmatrix} Y_{Fer,t-1} \\ Y_{LifeEx,t-1} \end{bmatrix} + \begin{bmatrix} \tau^2_{1,1} & \tau^2_{1,2} \\ \tau^2_{2,1} & \tau^2_{2,2} \end{bmatrix} \begin{bmatrix} Y_{Fer,t-2} \\ Y_{LifeEx,t-2} \end{bmatrix} + \begin{bmatrix} \tau^3_{1,1} & \tau^3_{1,2} \\ \tau^3_{2,1} & \tau^3_{2,2} \end{bmatrix} \begin{bmatrix} Y_{Fer,t-3} \\ Y_{LifeEx,t-3} \end{bmatrix} + \begin{bmatrix} \varepsilon_{Fer,t} \\ \epsilon_{LifeEx,t} \end{bmatrix} \qquad (1.4)$$

In scalar form:

$$Y_{Fer,t} = c_{Fer} + \tau^1_{1,1} Y_{Fer,t-1} + \tau^1_{1,2} Y_{LifeEx,t-1} + \tau^2_{1,1} Y_{Fer,t-2} + \tau^2_{1,2} Y_{LifeEx,t-2} + \tau^3_{1,1} Y_{Fer,t-3} + \tau^3_{1,2} Y_{LifeEx,t-3} + \varepsilon_{Fer,t} \qquad (1.5)$$

$$Y_{LifeEx,t} = c_{LifeEx} + \tau^1_{2,1} Y_{Fer,t-1} + \tau^1_{2,2} Y_{LifeEx,t-1} + \tau^2_{2,1} Y_{Fer,t-2} + \tau^2_{2,2} Y_{LifeEx,t-2} + +\tau^3_{2,1} Y_{Fer,t-3} + \tau^3_{2,2} Y_{LifeEx,t-3} + \varepsilon_{LifeEx,t} \qquad (1.6)$$

From equations (1.4) – (1.6), the c terms are intercepts, τ are the regression coefficients and ε represent error terms. Subscripts on each term denote their representative variable at a certain point of time and the superscripts denote nth number of lag. Equations (1.5) and (1.6) together form the VAR system. They can be estimated separately or via the OLS estimation (16).

The next step is to check stationary of the selected VAR model as a stationary VAR model is considered stable. Roots of characteristic polynomial of the companion matrix (i.e. matrix τ from equation (1.4)) are used for this purpose. If the eigenvalues of companion matrix are less than one, then the VAR model is stable. These eigenvalues can also be represented graphically in polar coordinates and for a stable VAR model, all its eigenvalues are found lying within the unit circle. This is known as the stationarity or stability condition(16,17).

VAR model and residual autocorrelation

A VAR model must include sufficient number of lags to ensure that its residuals are white noise, i.e. there are no residual autocorrelation. This helps determine if the selected model can describe data sufficiently. Residual autocorrelation determines the goodness of fit of the VAR model and presence of residual autocorrelation will indicate that the model has left some information out of account. For VAR models, the Lagrange Multiplier(LM) test can be employed to check for residual autocorrelation and it tests the null hypothesis of no autocorrelation (17).

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Methods of inferences

Interpreting estimates of a p-lag VAR model is difficult since it has many parameters and the difficulty accentuates when the value of p is large. Hence, summary measures such as Granger causality, impulse response analysis, and variance decomposition are employed to describe the dynamics among variables that the VAR model is comprised of. This paper is concerned with the first two methods and provides theoretical explanation for both below.

Granger causality

The Granger causality approach was first proposed by Clive Granger in 1969 (18) and contrary to its name, it is dedicated to detect predictive content of variables within the VAR model. That is, the test helps realize if one variable has useful information about future dynamics of other variable(s) in the model. In a bivariate VAR model such as equation (1.4),if $Y_{Fer,t}$ helps to predict $Y_{LifeEx,t}$ then $Y_{Fer,t}$ Granger-causes $Y_{LifeEx,t}$. Similarly, if $Y_{LifeEx,t}$ helps to predict $Y_{Fer,t}$then$Y_{LifeEx,t}$ Granger- causes $Y_{Fer,t}$. This can be tested using the Granger causality test which tests the null hypothesis of no Granger causality.

To test if $Y_{Fer,t}$ Granger-causes $Y_{LifeEx,t}$and $Y_{LifeEx,t}$ Granger-causes $Y_{Fer,t}$, the Granger causality test will first estimate equations (1.5) and (1.6) and then conduct F test on the following null hypotheses:

$$H_0: \tau_{1,2}^1 = \tau_{1,2}^2 = \tau_{1,3}^3 = 0 \text{ (from equation (1.5)}$$

$$H_0: \tau_{2,1}^1 = \tau_{2,2}^2 = \tau_{2,3}^3 \text{(from equation (1.6)}$$

Depending on whether the null hypotheses are rejected or not, running both the tests may yield an outcome from the following four scenarios: no Granger causality, one-way Granger causality from either direction or bilateral causality (also called feedback, this is Granger causality running from both directions). However, prediction does not equal causality and it is advised that results of Granger causality tests be interpreted with great caution.

Impulse response analysis

The impulse response analysis is another approach that examines interactions of variables in the VAR model. Contemporaneous association is likely to exist among variables that possess a dynamic relationship in the VAR model and this association becomes visible in the model's residuals(13). The impulse response function (IRF)traces out reactions of dependent variables over time to the shocks that hit the system through error terms (such as $\varepsilon_{Fer,t}$ and $\varepsilon_{LifeEx,t}$ in equations (1.5) and (1.6), respectively)(14).

To estimate an impulse response function, the VAR model must first be transformed to a vector moving average process. It will then be possible to trace shocks to the error terms relative to their impacts on the dependent variable. To illustrate, equation (1.3) transforms to:

$$Y_t = \mu + \varepsilon_t + \gamma_1 \varepsilon_{t-1} + \gamma_2 \varepsilon_{t-2} + \ldots \ldots \quad (1.7)$$

where, $\frac{\partial Y_t}{\partial \varepsilon_t'} = \gamma_s$ and s is time lag. The (*Fer*, *LifeEx*) component of γ_s $(i.e.\gamma_s^{Fer,LifeEx})$will capture the impacts of one unit shock to variable *LifeEx* at time t on variable *Fer* at time

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t+s. Hence, it is interpreted as the IRF(13). However, for this interpretation to be feasible the elements of error terms must be uncorrelated and this condition is fulfilled through recursive casual ordering. The recursive casual ordering posits that if $Y_t = (y_{1,t}, y_{2,t}, y_{3,t})$, then the variables of Y_t should be ordered in a way that $y_{1,t}$affects $y_{2,t}$and $y_{3,t}$ but not vice versa. Similarly, $y_{2,t}$affects $y_{3,t}$ but not $y_{1,t}$ and $y_{3,t}$ cannot affect $y_{1,t}$or $y_{2,t}$(13). Thus, the VAR model from equation (1.3) can be rewritten as:

$$y_{1,t} = \alpha_1 + \Phi_{1,1}Y_{t-1} + \Phi_{1,2}Y_{t-2} + \eta_{1,t} \quad (1.8)$$

$$y_{2,t} = \alpha_2 + \beta_{2,1}y_{1,t} + \Phi_{2,1}Y_{t-1} + \Phi_{2,2}Y_{t-2} + \eta_{2,t} \quad (1.9)$$

and then transformed into the Wold representation:

$$Y_t = \mu + \nabla_0 \eta_t + \nabla_1 \eta_{t-1} + \nabla_2 \eta_{t-2} + \cdots \quad (1.10)$$

The impulse response function can then be expressed as:

$$\frac{\partial y_{LifeEx,t+s}}{\partial \eta_{Fer,t}} = \omega^s_{LifeEx,Fer} \quad (1.11)$$

where, *LifeEx, Fer* =1,2,…..n and s>0.

Exposition of main material of research with complete substantiation of obtained scientific results. **Discussion**

Results

The ADF test results are shown in Table 1. Female life expectancy is stationary at its first difference and TFR is stationary at its level form. The stationary forms of the variables will be used to conduct analysis for this study. Furthermore, as the variables are stationary at different levels, they do not share a common stochastic trend and are not co-integrated.

Table 1. ADF Unit Root Test

Variables	Level		First Difference	
	No Trend	Trend	No Trend	Trend
Female Life Expectancy	-2.483	-2.554	-6.285**	-7.401**
Total Fertility Rate	-11.264**	-6.897**	-4.463 **	-6.058 **

Note: ***, ** and * denote respective significance at 1%, 5% and 10% critical levels.
Source: Produced by the author

To find optimal lag length *p* of the VAR model, I use AIC and SBIC. Both the criteria yield 3 as value for *p*. This implies that that VAR (3) model or equations (1.3) to (1.6) represent the suitable VAR model/system for this study. The next step is to check if this selected VAR (3) model is stable. For this purpose, I graphically present the eigenvalues of companion matrix in polar coordinates in Fig 1. All the eigenvalues are seen to lie within the unit circle which indicates that all the eigenvalues are less than one. Thus, the VAR (3) model chosen for this study it fulfills the stationarity or stability condition and is stable.

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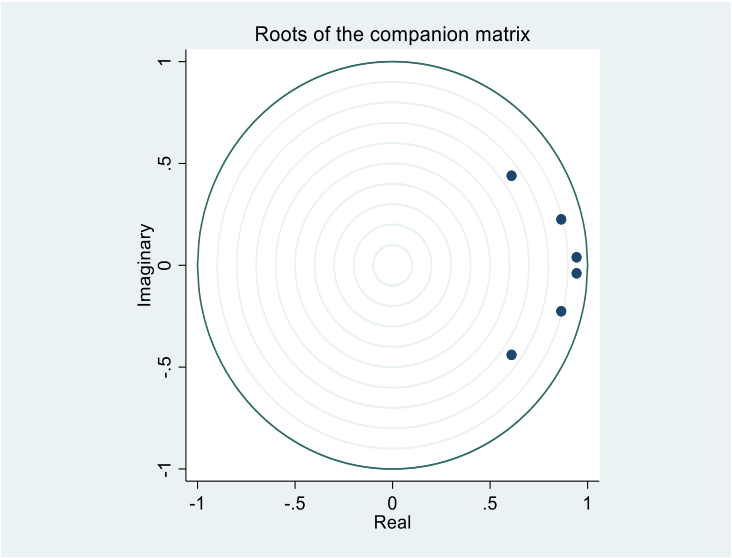
Fig 1. Eigenvalues of the companion matrix



Source: Produced by the author

To detect presence of residual autocorrelation within the VAR (3) model, I employ the Lagrange-Multiplier (LM) test that tests the null hypothesis of no autocorrelation at each lag order. Results of the LM test are presented in Table 2 and show that the null hypothesis cannot be rejected at first-and second-order at any critical levels. At the third-order, however, the null hypothesis cannot be rejected 1% critical level. Thus, I conclude that there is no autocorrelation in the VAR (3) model used in this study.

Table 2. Lagrange-Multiplier Test Results

Null Hypothesis	Lag Order	Chi-Square Statistic	p-value
No autocorrelation at lag order	1	5.4185	0.24698
	2	6.8569	0.14365
	3	9.6492**	0.04677**

Note: ***, ** and * denote respective significance at 1%, 5% and 10% critical levels.
Source: Produced by the author

The results of the Granger-causality test are shown in Table 3. A bilateral causality between the variables $Y_{LifeEx,t}$ and $Y_{Fer,t}$ is observed. The null hypothesis of no Granger-causality is rejected for both the variables and Granger causation is observed from both directions. Thus, it can be said that variable $Y_{LifeEx,t}$ is a useful predictor of $Y_{Fer,t}$ and similarly, $Y_{Fer,t}$ is a useful predictor of e $Y_{LifeEx,t}$.

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Table 3. Granger Causality Test Results

Null Hypothesis	Chi-Square Statistic	p-value
$Y_{LifeEx,t}$ does not Granger cause $Y_{Fer,t}$	21.537**	0.000
$Y_{Fer,t}$does not Granger cause $Y_{LifeEx,t}$	45.522**	0.000

Note: ***, ** and * denote respective significance at 1%, 5% and 10% critical levels.
Source: Produced by the author

The estimation results from VAR (3) model are presented in Table 4. In the TFR equation, the variable TFR ($Y_{Fer,t}$) is regressed on the lags of the variable female life expectancy ($Y_{LifeEx,t-1}, Y_{LifeEx,t-2}, Y_{LifeEx,t-3}$) and on its own lags($Y_{Fer,t-1}$, $Y_{Fer,t-2}$, $Y_{Fer,t-3}$,). Results show that ceteris paribus, only the third lag of $Y_{LifeEx,t}$exerts a statistically significant and negative impact on$Y_{Fer,t}$ at 10% critical level. On the other hand, $Y_{Fer,t}$ is strongly affected by its past values and the impact of each lag is statistically significant at 5% critical level.

Table 4. Estimation Results of the VAR (3) Model

	$Y_{Fer,t}$		$Y_{LifeEx,t}$	
	Coefficients	Standard Errors	Coefficients	Standard Errors
Constant	0.0028	0.001**	0.0019	0.0060
$Y_{LifeEx,t-1}$	-0.0082	0.0124	2.0629	0.0744**
$Y_{LifeEx,t-2}$	0.0218	0.0195	-1.6126	0.1166**
$Y_{LifeEx,t-3}$	-0.0170	0.0092*	0.4711	0.0553**
$Y_{Fer,t-1}$	2.7736	0.0795**	0.9743	0.4762**
$Y_{Fer,t-2}$	-2.5895	0.1517**	-2.0824	0.9089**
$Y_{Fer,t-3}$	0.8147	0.0729**	1.1143	0.4371**
R^2	1.0000		0.9986	
RMSE	0.001301		0.007798	
P>chi2	0.0000		0.0000	

Note: ***, ** and * denote respective significance at 1%, 5% and 10% critical levels.
Source: Produced by the author

In the female life expectancy equation, the variable female life expectancy ($Y_{LifeEx,t}$) is regressed on its own lags($Y_{LifeEx,t-1}, Y_{LifeEx,t-2}, Y_{LifeEx,t-3}$)and on the lags of TFR ($Y_{Fer,t-1}$, $Y_{Fer,t-2}$, $Y_{Fer,t-3}$,). Results show that ceteris paribus, the second lag of TFR has a strong and negative impact on $Y_{LifeEx,t}$ but the other two lags of $Y_{Fer,t}$exert positive impacts on $Y_{LifeEx,t}$.All these effects are statistically significant at 5% critical level. $Y_{LifeEx,t}$ is also strongly affected by its own past values and impacts of all the lags are also statistically significant at 5% critical level.

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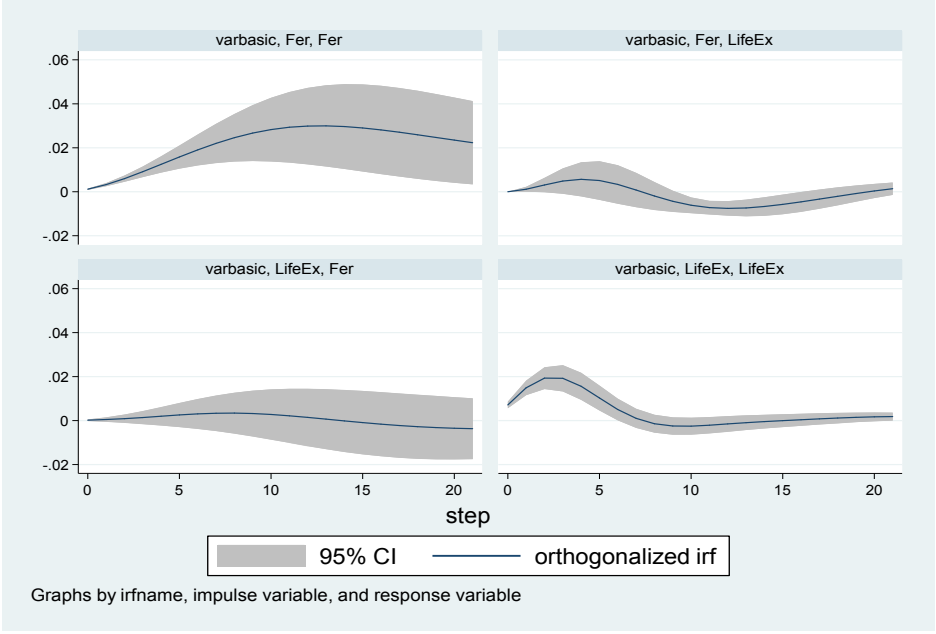
Overall, results from Table 4 imply that TFR is hardly affected by the variable female life expectancy whereas the impact of TFR on female life expectancy is strong and statistically significant. These inferences can be further supported through analysis of impulse response functions (IRFs).

Fig 2 graphically presents the orthogonalized IRFs over a 20-year time period. The diagonal panels (top -left and bottom -right) show the effects of shocks to each respective variable on their respective future values. The off-diagonal panels (i.e. top-right and bottom-left) however, depict the effects of shocks to one variable onto the other variable. I will analyze the off-diagonal panels first.

Fig 2. The orthogonalized impulse response functions



Source: Produced by the author

The top-right panel shows response of female life expectancy to a one standard deviation shock to the TFR. There is no effect at zero lag (i.e. current period) but from period 1, female life expectancy rises gradually at a 0.01 percentage point increase until it peaks at the 5thperiod. After the 5th period, female life expectancy declines persistently for five more periods. From the 10thperiod, the decline then levels off at a 0.01 percentage point decrease until a gradual increase in the variable is observed from period 15. This increase continues for few time periods until the shock dies out, i.e. the impact converges back to 0. Overall, the panel depicts that female life expectancy responds strongly to the TFR shock. In the short run, a one standard deviation shock to the TFR may exert a positive

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impact on female life expectancy but in the long run, this impact will be persistently negative until the shock dies off eventually. A very different scenario is observed in the bottom-left panel which shows response of TFR to a one standard deviation shock in female life expectancy. No response of TFR is observed from the initial stages of the impulse to period 10. After the 10th period, fertility rate begins to decline steadily until it levels off at a 0.01 percentage point decrease. Overall, this panel shows that TFR responds weakly to the female life expectancy shock.

Next I will briefly describe what the diagonal panels (top -left and bottom -right) depict. The top-right panel shows that a rise in TFR after the initial impulse and this rise persists up to period 10. After the 10th period, TFR rapidly levels off at 0.03 percentage point increase. Thus, a one standard deviation shock to the TFR exerts positive impact on its future values both in the short and long run. The bottom –right panel shows that female life expectancy experiences a strong but short positive impact from one standard deviation shock in female life expectancy. The impact begins to wane initially after the 5th period and then quickly converges back to 0. Thus, a one standard deviation shock in female life expectancy causes positive impact on its future values in the short run but no effects are visible in the long run.

Discussion

This study has used data from Bangladesh over the years 1973-2019 and bivariate VAR (3) model to demonstrate a negative association between female life expectancy and TFR. Both the time series variables are significantly affected by their own past values. The results also indicate presence of bilateral Granger-causality between the variables implying that both variables are useful in forecasting one another. Furthermore, the IRFs show that female life expectancy reacts strongly to a one standard deviation shock to TFR and is seen to decline persistently in the long run until the shock to TFR dies off. On the contrary, a one standard deviation shock to female life expectancy barely exerts any significant impact on the TFR, especially in the long run.

Results yielded by the IRFs have important implications for Bangladesh. Female life expectancy and TFR share an inverse correlation in this developing country and a one standard deviation shock to TFR leads to a substantial and negative impact on female life expectancy over time.

Better access to contraception and family planning (FP) advices have played key role in substantially lowering the TFR in Bangladesh. In recent years, however, both the CPR and TFR have stagnated which implies greater need for greater attention on demand for FP services. Furthermore, the advent of COVID-19 pandemic has limited access to FP information and severely disrupted the utilization of FP services(19,20). The decline in FP use among married women of reproductive age (15-49 years) was 23% in Bangladesh(19). From 2019-2020, the annual decline in use of short-term and long-acting methods were 14% and 32%, respectively. The drop in use of permanent FP methods has been highest since the pandemic with an annual 33% decline in use since 2019 (20). Compounded, these phenomena could act as shocks to the TFR and so, in accordance with findings of this study, adversely affect female life expectancy via TFR. It is possible that shocks to the TFR from decline in use of all forms of FP methods during COVID-19 pandemic may lead to lower life expectancy for Bangladeshi women in future.

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Pre-existing inadequate number of field-level workers which further exacerbated during the pandemic, age and education level of women, working status of the household head, number of living and dead children, locality are some of the prominent factors led to reduced use of FP methods during COVID-19 (19,20) . Regular recruitment, training and deployment of field-level workers to counsel women on FP methods and adopting pragmatic approaches within the FP programs could enhance recovery of FP use and cushion the TFR from being affected by shocks from decreased use of FP.

Conclusions

In conclusion, this study shows that in Bangladesh, female life expectancy and TFR exhibit a negative association with TFR exerting strong impact on female life expectancy. TFR is associated with greater empowerment of women and high female life expectancy can be considered as an indicator of development vis-à-vis women. Given the evidence, it is recommended that attempts be taken to cushion the TFR and enhance development as well as empowerment of women. However, there is an urgent need for further research in support of this inference for Bangladesh and other developing countries alike.

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