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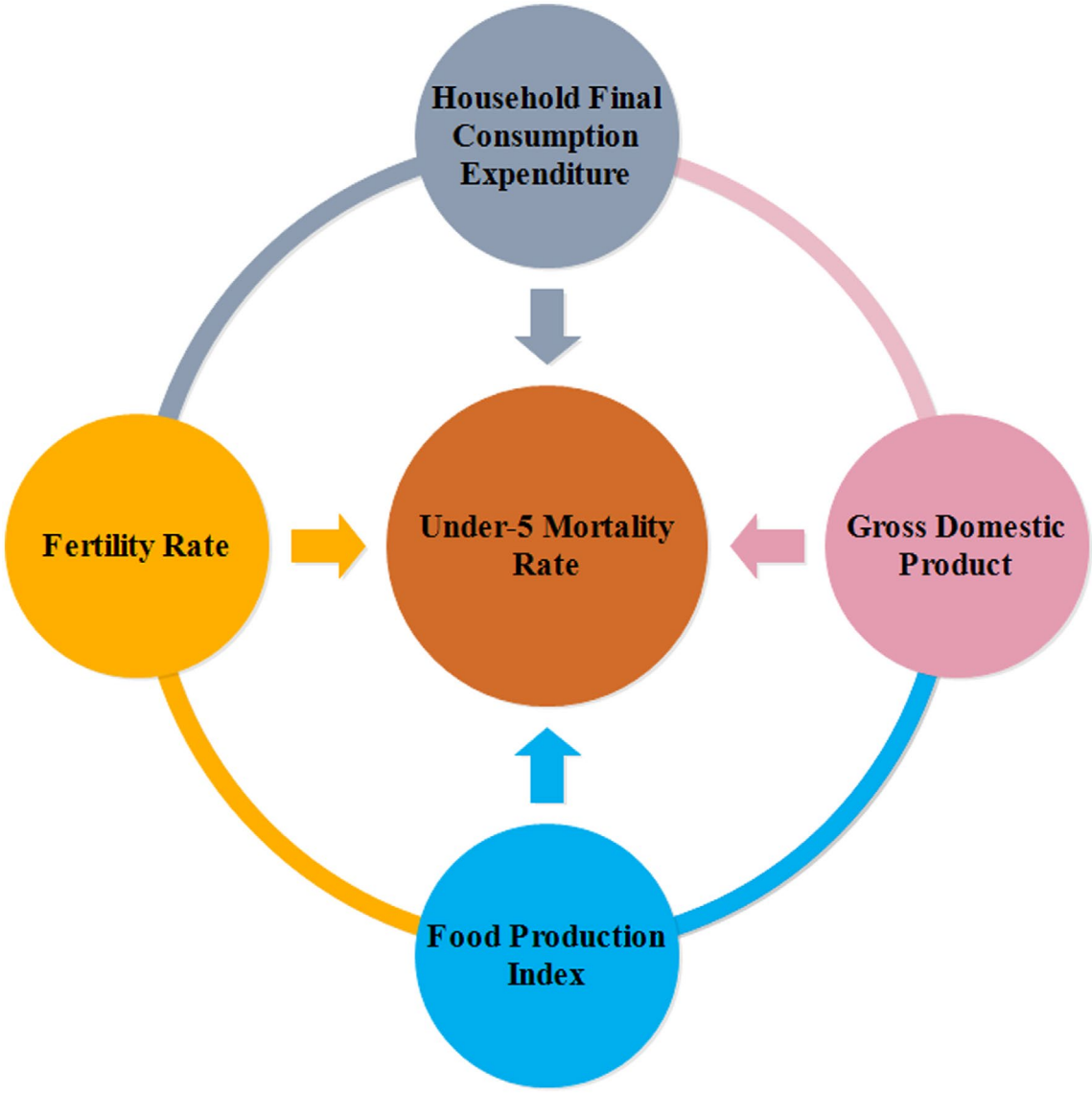

ECONOMETRICS | RESEARCH ARTICLE

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The casual nexus between child mortality rate, fertility rate, GDP, household final consumption expenditure, and food production index

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Abstract: In this study, the causal nexus between child mortality rate, fertility rate, GDP, household final consumption expenditure, and food production index in Ghana was investigated spanning from 1971 to 2013 using the Autoregressive and Distributed Lag (ARDL) method. The study tested for unit root, ARDL bounds cointegration test, ARDL long-run elasticities, Granger causality, and Variance Decomposition Analysis using Cholesky technique. There was evidence of long-run equilibrium relationship running from fertility rate, food production index, GDP, and household final consumption expenditure to the mortality rate. There was evidence of a bidirectional causality running from household final consumption expenditure to fertility rate. Evidence from the Variance Decomposition Analysis shows that, almost 6% of future fluctuations in mortality rate are due to shocks in the food production index, while 2% of future fluctuations in mortality rate are due to shocks in fertility rate. Evidence from the study shows that the increasing levels of social determinants like Gross Domestic Product and Household final consumption expenditure will help reduce child mortality rates in Ghana. In order to reduce child mortality rates among children under-5, infants and vulnerable in Ghana, there is the need to end hunger and ensure access to safe and nutritious food.

Samuel Asumadu-Sarkodie

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PUBLIC INTEREST STATEMENT

Five in 10 of global under-5 deaths occur in sub-Saharan Africa and 45% of all under-5 deaths happen in the first 28 days of the child's life. Causes of child mortality have been associated with nutrition and health care delivery. However, other social, economic, and environmental factors contribute to this global issue. In this case, a multidisciplinary approach towards the analysis of the causal effect of child mortality rates is important. In view of this, the study analyzes the causal nexus between child mortality rate, fertility rate, GDP, household final consumption expenditure, and food production index in Ghana using modern econometric methods like Granger causality, ARDL cointegration test, and Variance Decomposition Analysis to examine the long-run relationships between the variables of interest. The outcome of the study will serve as an informative tool for policy-makers in Ghana and set a foundation for future research in this field.

Subjects: Allied Health; Child and Family Social Work; Economics; Health & Society; Health and Social Care; Health Conditions; Nutrition and Dietetics; Public Health Policy and Practice; Social Work and Social Policy; Statistics for Social Sciences

Keywords: mortality rate; fertility rate; cointegration; Ghana; health econometrics; Variance Decomposition Analysis; Granger causality; food production index; health care

JEL classification: I11; I12; I18

1. Introduction

Child mortality has gained global prominence since 1990, progress has been made in reducing child mortality throughout the world (UN Inter-agency Group for Child Mortality Estimation, 2015). The emergence of the Millennium Development Goal (MDG) four sought to reduce child mortality by about two-thirds of the existing morality rates by the end of 2015. Progress has been made towards MDG four, according to the 2015 MDGs Report by the (United Nations, 2015a), the global under-5 mortality rate declined by more than half, dropping from 90 to 43 deaths per 1,000 livebirths between 1990 and 2015. Regardless of population growth in developing regions, global under-5 deaths declined from 12.7 million in 1990 to almost 6 million in 2015. The global rate of reduction in under-5 has more than tripled since the early 1990s. Sub-Saharan Africa experienced over five times faster annual rate of reduction in under-5 during 2005–2013 than in 1990–1995.

According to a press release by World Bank (World Bank, 2015a), almost one-third of the world's countries (62/195) has met the MDG-4 which target to reduce under-5 mortality by two-thirds. The annual reduction rate of mortality has increased from 1.8% in 1990–2000 to 3.9% in 2000–2015. Two-thirds of Africa's countries, among the 10 of the 12 low income countries have reduced under-5 mortality rate. Five in 10 global under-5 deaths occur in sub-Saharan Africa and 45% of all under-5 deaths happen in the first 28 days of the child's life. Simply put, on the day of birth one million neonatal deaths occur while almost two million children die in the first week of life. Nevertheless, under-5 mortality rate in sub-Saharan Africa has registered a substantive acceleration by an increase in annual reductions of 1.6% in 1990s to 4.1% in 2000–2015.

According to (UNICEF, 2015a) there is a 53% drop in under-5 mortality rate, however, 16,000 children under-5 still die everyday, which is not enough to meet MDG-4 of two-thirds reduction between 1990 and 2015. As the MDG era ends, world leaders have renewed their commitment towards improving child survival by launching Committing to Child Survival: A Promise Renewed that aims for a continual post-2015 focus to end preventable child deaths. The launch of the renewed Global Strategy for Women's, Children's and Adolescent's Health will serve as a roadmap to achieve the Sustainable Development Goal (SDG) 3: "Ensure healthy lives and promote well-being for all at all ages" (United Nations, 2015b).

UNICEF (2015a) suggests that an evidence-based estimation of child mortality is a keystone for tracing the progress towards child survival goals and for national policy planning and global health strategies, approaches and interventions on child health and well-being.

A vast number of studies have shown that significant progress has been made towards reducing global child mortality from 1990 to 2015 (Alkema, New, Pedersen, & You, 2014; Hill, You, Inoue, & Oestergaard, 2012; McArthur, 2014; Wang et al., 2014; You et al., 2015). You et al. (2015) provided estimates of under-5 mortality spanning from 1990 to 2015 for 195 countries and further projected 2016–2030 based on a construct scenario with Bayesian B-spline bias-reduction model to provide insights into the burden of the post-MDG 4 (2015). Their study concluded that 116 of the 195 countries representing 56% have already achieved the SDG-3 target with under-5 mortality rate of 25 or fewer deaths per 1,000 live births. Liu et al. (2015) investigated the distributions of the causes of child mortality in neonates and children aged 1–59 months using vital registration-based multiclausal models for countries with low under-5 mortality and verbal autopsy-based multiclausal

models for high under-5 mortality countries. Their study concluded that sub-Saharan Africa will increase under-5 birth and death rate from 25 to 50% in 2013 to 33 and 60% in 2030.

Our study is in line with Aakvik and Holmås (2006) who investigated the impact of economic conditions and access to primary health care outcomes in Norway. They employed a dynamic panel data model using data spanning from 1986 to 2001 to estimate the fixed effects of mortality and the number of general practitioners. Their study concluded that no relationship exists between mortality and the number of general practitioners in Norway. Nevertheless, the number of variables (2) and the period of the data (15 observations) employed in the study make it difficult to have a conclusion that represents the population. Hill, Zimmerman, and Jamison (2015) investigated the global and regional mortality estimates for children aged 5–14 years in low and middle income countries using regression analysis. Their study concluded that mortality rates in low and middle income countries reduced from about 2.4 million in 1990 to about 1.5 million in 2010. Jacob, Ludwig, and Miller (2013) estimated the causal effects of housing and neighborhood on child mortality using data spanning from 1997 to 2009. Their study concluded that moving from a high-poverty public housing in Chicago leads to a large decline in mortality rates. Leigh and Jencks (2007) assessed the relationship between economic inequality and mortality rate in rich countries using a panel data spanning from 1903 to 2003. Using a fixed effects specification shows that a higher GDP is associated with lower mortality rates.

Almost all the studies employ traditional estimation methods rather than modern-day econometric methods like Dynamic Ordinary Least Squares (DOLS), Fully Modified Ordinary Least Squares (FMOLS), Vector Error Correction Model (VECM), and Autoregressive and Distributed Lag (ARDL). It is therefore difficult to establish a long-run causal relationship between health outcomes and social causes.

The causal relationship between health outcomes and social causes has been sporadic and limited, especially in developing countries like Ghana. Ghana, as a growing economy from lower middle income to a middle-income economy, has suffered many drawbacks in the field of energy (Asumadu-Sarkodie & Owusu, 2016a, 2016e, 2016f), water management (Asumadu-Sarkodie, Owusu, & Jayaweera, 2015; Owusu, Asumadu-Sarkodie, & Ameyo, 2016), environmental pollution (Asumadu-Sarkodie & Owusu, 2016c; Owusu & Asumadu-Sarkodie, 2016) and health (Asumadu-Sarkodie & Owusu, 2015). Ghana's under-5 mortality rate is 78 deaths per 1,000 live births leading to a total of 62,000 under-5 deaths (UNICEF, 2015b). One of the factors of poor health outcomes in Ghana is a limited scientific research in the health sector that will assist Governmental bodies, non-Governmental organisations, local and private investors with the required information to make decisive choices in their investment in Ghana's health sector. Attempts to unveil the health, developmental issues in Ghana in the scientific space have been sporadic and limited. Therefore, a multidisciplinary approach that tackles the health issues in Ghana in the scientific space would help in nation building.

To the best of our knowledge, our research is the first of its kind in the scope of the study and will therefore contribute to the existing literature on health economics. The aim of the study is to examine the causal nexus between child mortality rate, fertility rate, GDP, household final consumption expenditure, and food production index in Ghana using ARDL method with data spanning from 1960 to 2013. As part of the methodology, the study examines the long-run equilibrium relationship, the Granger causality to determine the direction of causality, and the Variance Decomposition Analysis using Cholesky technique which is our contribution to existing literature in health economics. Using the concept adopted by Asumadu-Sarkodie, Owusu, and Rufangura (2015), the study will increase the awareness of the social causes of child mortality, avoid future deaths, alleviate the social causes, and assist on how child mortality can be managed to end preventable child deaths as a roadmap to achieve the SDG (3).

2. Methodology

The study investigates the causal nexus between child mortality rate, fertility rate, GDP, household final consumption expenditure, and food production index in Ghana using the ARDL. A time series data-set spanning from 1971 to 2013 was employed from the World Bank database (World Bank, 2015b). Five study variables were used in the study, which include: MR—Mortality rate, under-5 (per 1,000 live births), FR—Fertility rate, total (births per woman), GDP—Gross Domestic Product (constant 2005 US$), HFCE—Household final consumption expenditure (current US$), and FPI—Food production index (2004–2006 = 100). The selection of the variables is based on the SDGs 1–3 and 8 (United Nations, 2015b).

Prior to testing for Variance Decomposition Analysis using Cholesky technique, we tested for unit roots, performed Granger causality tests, ARDL bounds test, and model diagnostics. Engle-Granger, Johansen's method (Johansen, 1995), or single-equation methods like DOLS, FMOLS, and ARDL models have been used in econometrics to study the long-run and cointegration between variables, which as a requirement, all variables must be I(1) or a prior knowledge and specification requirement of variables are I(0) and I(1). Nevertheless, Pesaran and Shin (1998) showed that cointegration among variables can be estimated as an ARDL model with the variables in cointegration at either I(0) or I(1) without pre-specification of variables which are either I(0) or I(1). Furthermore, Pesaran and Shin (1998) maintain that ARDL model can have different number of lag terms without the requirement of symmetry lag lengths like other cointegration estimation methods.

The model specification for the study is expressed as:

$$\mathrm{LMR}_t = \beta_0 + \beta_1 \mathrm{LFR}_t + \beta_2 \mathrm{LGDP}_t + \beta_3 \mathrm{LHFCE}_t + \beta_3 \mathrm{LFPI}_t + \varepsilon_t \tag{1}$$

where LMR, LFR, LGDP, LHFCE, and LFPI represent the logarithmic transformation of MR—Mortality rate, FR—Fertility rate, GDP—Gross Domestic Product, HFCE—Household final consumption expenditure, and FPI—Food production index since the logarithmic transformation leads to a more stable data variance in year t, ε_t is the error term and β_0, β_1, β_2, β_3, and β_4 are the elasticities to be estimated.

Following the existing literature (Asumadu-Sarkodie & Owusu, 2016b, 2016d; Asumadu-Sarkodie and Owusu, 2016g), the ARDL model for the present study can be expressed as:

$$\begin{aligned}\Delta \mathrm{LMR}_t = {} & \alpha_0 + \delta_1 \mathrm{LMR}_{t-1} + \delta_2 \mathrm{LFR}_{t-1} + \delta_3 \mathrm{LGDP} + \delta_4 \mathrm{LHFCE}_{t-1} + \delta_5 \mathrm{LFPI}_{t-1} + \sum_{i=1}^{p} \beta_1 \Delta \mathrm{LMR}_{t-i} \\ & + \sum_{i=0}^{p} \beta_2 \Delta \mathrm{LFR}_{t-i} + \sum_{i=0}^{p} \beta_3 \Delta \mathrm{LGDP}_{t-i} + \sum_{i=0}^{p} \beta_4 \Delta \mathrm{LHFCE}_{t-i} + \sum_{i=0}^{p} \beta_5 \Delta \mathrm{LFPI}_{t-i} + \varepsilon_t\end{aligned} \tag{2}$$

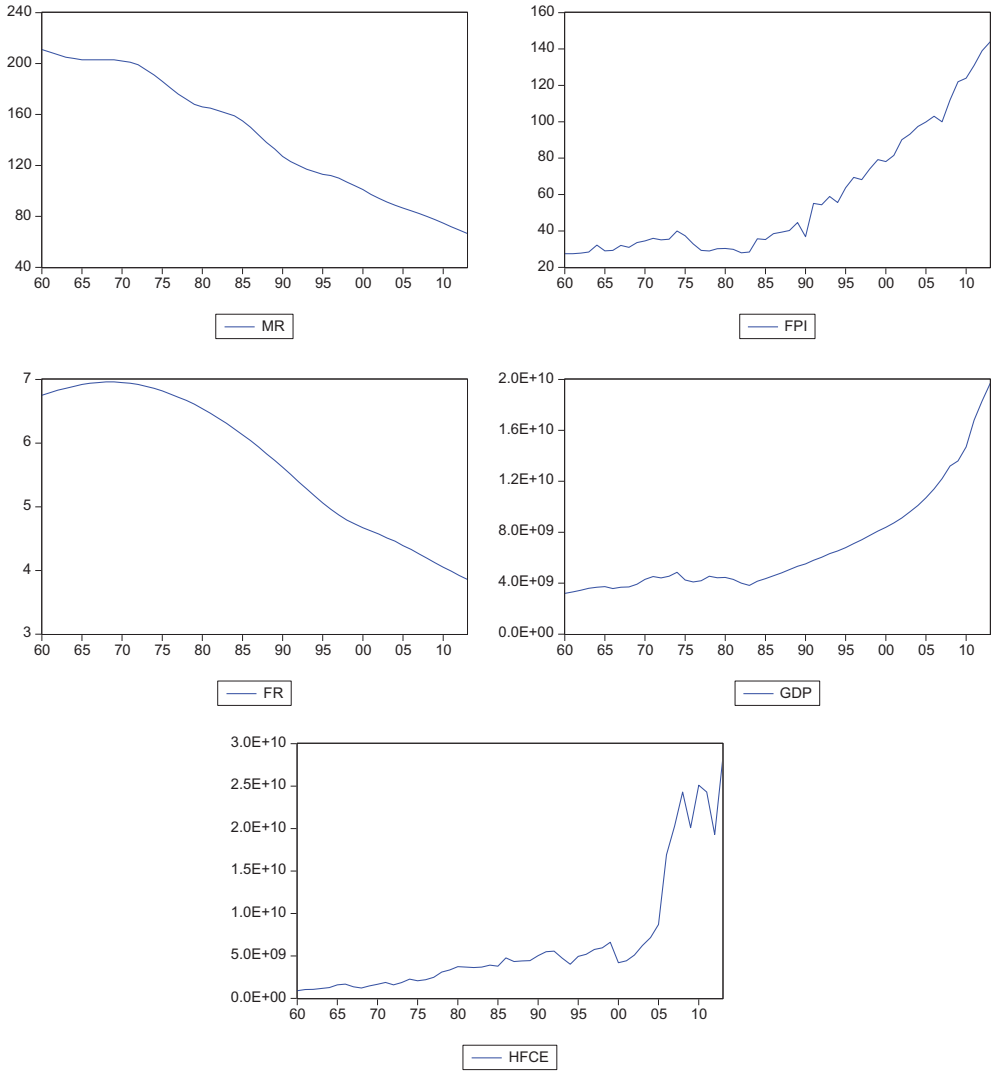
where α represents the intercept, t denotes year, p represents the lag order, ε_t represents the error term, and Δ represents the first difference operator.

The long-run equilibrium relationship between the series are examined using the *F*-tests based on the null hypothesis of no cointegration between LMR, LFR, LGDP, LHFCE, and LFPI [H_0:$\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$] against the alternative hypothesis of cointegration between LMR, LFR, LGDP, LHFCE, and LFPI [H_1:$\delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq 0$]. Using the *F*-test, the null hypothesis is rejected if the *F*-statistic lies above the upper bound or, the null hypothesis cannot be rejected if the *F*-statistic lies below the lower bound (Pesaran, Shin, & Smith, 2001).

3. Results and discussion

Figure 1 shows the trend of the study variables before logarithmic transformation. It is evident that as GDP, HFCE, and FPI increases periodically, MR and FR decreases periodically. At this moment, it is difficult to explain the reasons for the trend exhibited by the variables.

Figure 1. Trend of variables.



3.1. Descriptive analysis

This section outlines the descriptive statistical analysis of the study variables. Table 1 shows the descriptive statistical analysis of the study variables. While LGDP, LHFCE, and LFPI have a long-right tail (positive skewness), MR and FR have a long-left tail (negative skewness). However, all the variables show a platkurtic distribution. Jarque–Bera test statistic functions under the null hypothesis of normal distribution. With the exception of LGDP, all the variables are normally distributed based on 5% *p*-value therefore we cannot reject the null hypothesis. Evidence from the statistics shows that only LFR shows a monotonic relationship with LMR, however LGDP, LHFCE, and LFPI are negatively associated with.

3.2. Unit root test

We employ the augmented Dickey–Fuller (ADF) (Dickey & Fuller, 1979) unit root test in the study. Table 2 presents the results of the ADF unit root test. At level, we cannot reject the null hypothesis based on 5% *p*-value. The model proposed is stationary at level, but non-stationary at first difference based on 5% *p*-value.

Table 1. Descriptive analysis

	LMR	LFPI	LFR	LGDP	LHFCE
Mean	4.908218	3.905867	1.728512	22.51059	22.12644
Median	4.990224	3.660941	1.790057	22.29706	22.13645
Maximum	5.351858	4.969813	1.940179	23.70388	24.06613
Minimum	4.197202	3.314186	1.350667	21.88642	20.60336
Std. Dev.	0.36216	0.535588	0.199237	0.493134	0.910702
Skewness	−0.381941	0.578126	−0.458749	0.839331	0.488432
Kurtosis	1.804315	1.862676	1.706235	2.591866	2.646705
Jarque Bera	4.52965	5.918451	5.660163	6.715073	2.427927
Probability	0.103848	0.051859	0.059008	0.034821	0.297018
LMR	1				
LFPI	−0.962459	1			
LFR	0.993102	−0.974337	1		
LGDP	−0.967895	0.981037	−0.967286	1	
LHFCE	−0.940798	0.877403	−0.910984	0.922604	1

Table 2. Augmented Dickey-Fuller unit root test

	LMR		LFPI		LFR		LGDP		LHFCE	
ADF level	**Test statistic**	**Prob**	**Test statistic**	**Prob**	**Test statistic**	**Prob**	**Test statistic**	**Prob**	**Test statistic**	**Prob**
None	−2.3275	0.0208	3.3788	0.9997	−2.1514	0.0315	2.9653	0.9990	2.7832	0.9984
Intercept	3.1197	1.0000	1.1363	0.9973	0.2190	0.9712	3.4496	1.0000	−0.0207	0.9521
Trend and intercept	−3.5219	0.0485	−1.1625	0.9076	−2.9449	0.1581	0.7789	0.9996	−1.8207	0.6806
ADF 1st difference										
None	1.3800	0.9560	−8.3267	0.0000*	−0.5236	0.4848	−3.3945	0.0011*	−5.9672	0.0000*
Intercept	−1.7049	0.4220	−9.6202	0.0000*	−2.1389	0.2309	−4.6526	0.0004*	−6.7100	0.0000*
Trend and intercept	−5.2320	0.0005*	−9.9629	0.0000*	−1.9908	0.5917	−5.4727	0.0002*	−6.6908	0.0000*

*Denotes rejection of the hypothesis at the 0.05 level.

3.3. ARDL cointegration test, long-run, and model selection

The ARDL model cointegration test as proposed by Pesaran et al. (2001) is calculated in the study based on the following equation:

$$Cointeq = LMR - (0.1315 * LFPI + 1.6066 * LFR - 0.1792 * LGDP - 0.0082 * LHFCE + 5.8694) \quad (3)$$

Table 3 presents a summary of the ARDL Bounds test cointegration. Evidence from Table 3 shows that the null hypothesis of no cointegration is rejected at 5% significance level. With the existence of a cointegration between the variables, the study selects an optimal model for the long-run relationship estimation. In Figure 2, the model selection criterion is given. Akaike information criterion selects the best model with the specification: ARDL (2, 3, 3, 4, 0).

Using the optimal model, the long-run equilibrium relationship between the variables is estimated. Table 4 shows that the error correction term [ECT (−1)=−0.3075, ρ = 0.0000] is negative and significant, showing evidence of a long-run equilibrium relationship running from LFR, LGDP, LHFCE and LFPI to LMR. The individual long-run effect between LMR and LFPI, LMR and LFR, and LMR and LGDP are statistically significant.

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Table 3. Cointegrating form and long run coefficients

Test statistic	Value	*k*
F-statistic	6.11019	4
Critical value bounds		
Significance (%)	I0 Bound	I1 Bound
10	2.45	3.52
5	2.86	4.01
2.50	3.25	4.49
1	3.74	5.06

Figure 2. Akaike information criterion model selection.

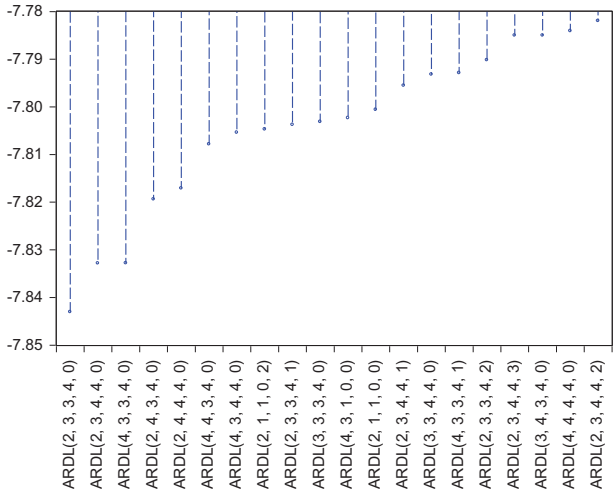

Table 4. Cointegrating form and long run coefficients

Cointegrating form				
ECT (−1)	−0.3075	0.0585	−5.2580	0.0000*
Long run coefficients				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LFPI	0.1315	0.0435	3.0226	0.0048*
LFR	1.6066	0.0816	19.6849	0.0000*
LGDP	−0.1792	0.0464	−3.8596	0.0005*
LHFCE	−0.0082	0.0112	−0.7318	0.4695
C	5.8694	0.7820	7.5054	0.0000*

*Denotes rejection of the hypothesis at the 0.05 level.

The long-run elasticities in Table 4 have policy implications in Ghana. Evidence from Table 4 shows that a 1% increase in Food production index will increase child mortality by 0.13% in the long-run, a 1% increase in Fertility rate will increase child mortality by 1.61% in the long-run, a 1% increase in Gross Domestic Product will decrease child mortality by 0.18% in the long-run, and a 1% increase in Household final consumption expenditure will decrease child mortality by 0.01% in the long-run. In other words, developed countries with higher economic growth have lower levels of child mortality rates. In this way, governmental policies in developing and least developed countries that promote economic growth would increase household final consumption expenditure which will directly affect health outcomes leading to a reduction in reported cases of child mortality.

After establishing a long-run relationship with ARDL, we ascertain the direction of the causal relationships between LMR, LFPI, LFR, LGDP, and LHFCE using the Granger causality test (Granger, 1988). Table 5 presents a pairwise Granger causality test between LMR; LFPI, LFR, LGDP, and LHFCE. It is evident from Table 5 that the null hypothesis; LMR does not Granger Cause LFPI, LMR does not Granger Cause LFR, LFR does not Granger Cause LFPI, LHFCE does not Granger Cause LFR, and LFR does not Granger Cause LHFCE are rejected at 5% significance level.

3.4. Diagnostic test for the ARDL model

ARDL Model was subjected to a series of diagnostic tests. Table 6 shows the diagnostic tests of the ARDL Model.

Residual Autocorrelation was tested using Heteroskedasticity Test based on Null Hypothesis: no autocorrelation at lag order *h*. Results from Breusch-Pagan-Godfrey Heteroskedasticity Test in Table 6 shows that the null hypothesis cannot be rejected at 5% significance level, meaning that no autocorrelation exists.

Table 5. Pairwise Granger causality test

Null hypothesis:	*F*-Statistic	Prob.
LFPI does not Granger Cause LMR	1.4179	0.2452
LMR does not Granger Cause LFPI	3.3673	0.0180*
LFR does not Granger Cause LMR	0.7483	0.5648
LMR does not Granger Cause LFR	4.7697	0.0030*
LGDP does not Granger Cause LMR	0.1852	0.9448
LMR does not Granger Cause LGDP	1.5886	0.1956
LHFCE does not Granger Cause LMR	1.3368	0.2726
LMR does not Granger Cause LHFCE	1.1390	0.3517
LFR does not Granger Cause LFPI	3.5270	0.0146*
LFPI does not Granger Cause LFR	0.2511	0.9073
LGDP does not Granger Cause LFPI	0.8332	0.5120
LFPI does not Granger Cause LGDP	0.6469	0.6322
LHFCE does not Granger Cause LFPI	0.9086	0.4680
LFPI does not Granger Cause LHFCE	1.7954	0.1483
LGDP does not Granger Cause LFR	0.5057	0.7317
LFR does not Granger Cause LGDP	1.4395	0.2383
LHFCE does not Granger Cause LFR	2.8683	0.0349*
LFR does not Granger Cause LHFCE	5.1899	0.0018*
LHFCE does not Granger Cause LGDP	0.8214	0.5191
LGDP does not Granger Cause LHFCE	1.3993	0.2512

*Denotes rejection of the hypothesis at the 0.05 level.

Table 6. Diagnostics of ARDL model

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	0.733216	Prob. F(16,33)	0.7418
Breusch-Godfrey Serial Correlation LM Test			
F-statistic	1.141969	Prob. F(2,31)	0.3323
Ramsey RESET Test			
	Value	**df**	**Probability**
F-statistic	0.703439	(1,32)	0.4079

Residual Serial Correlation was tested using Lagrange multiplier test based on Null Hypothesis: no serial *correlation at lag order h*. Results from Breusch–Godfrey Serial Correlation LM Test in Table 6 shows that the null hypothesis cannot be rejected at 5% significance level, meaning that no serial correlation exists.

Residual Functional Misspecification was tested using Ramsey RESET Test based on Null Hypothesis: no functional misspecification. Results from Ramsey RESET Test in Table 6 shows that the null hypothesis cannot be rejected at 5% significance level, meaning that the model is in its functional form.

Residual Normality was tested using Jarque-Bera test based on Null Hypothesis: residuals are multivariate normal. Results from Jarque-Bera test in Figure 3 shows that, the null hypothesis cannot be rejected at 5% significance level, meaning that the residuals are normally distributed.

3.5. Robustness of the ARDL model

The CUSUM and CUSUM of Squares tests are used to ascertain the parameter instability of the equation employed in the ARDL Model. Figures 4 and 5 show the CUSUM and CUSUM of Squares tests for parameter instability in the ARDL Model. Since the plots in CUSUM and CUSUM of Squares tests lie within the 5% significance level, the parameter of the equation is stable enough to estimate the long-run causality in the study.

3.6. Variance decomposition

The variance decomposition provides information on how each random innovation affects the variables. Tables 7–11 report the results of the variance decomposition of LMR, LFPI, LFR, LGDP, and LHFCE within a 10-period horizon. From Table 7, almost 6% of future fluctuations in mortality rate are due to shocks in the food production index, while 2% of future fluctuations in mortality rate are

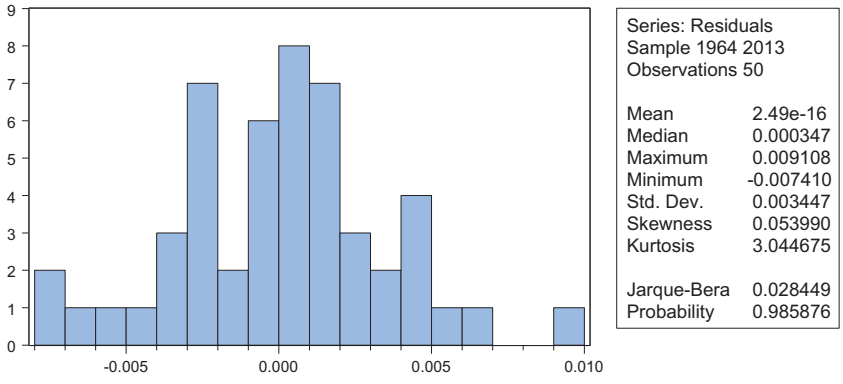

Figure 3. Normality test with Jarque-Bera statistic.

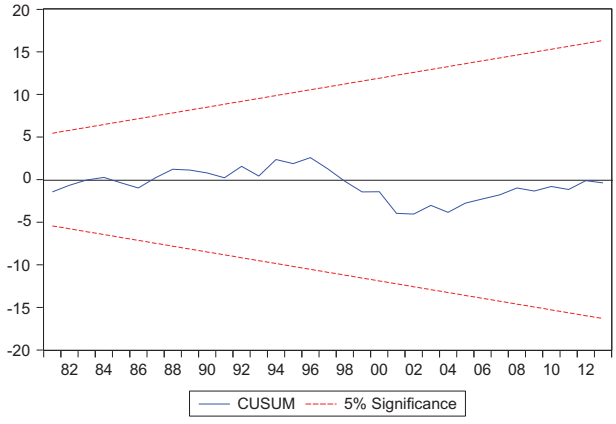

Figure 4. Stability test of ARDL model using CUSUM.

Figure 5. Stability test of ARDL model using CUSUM of squares.

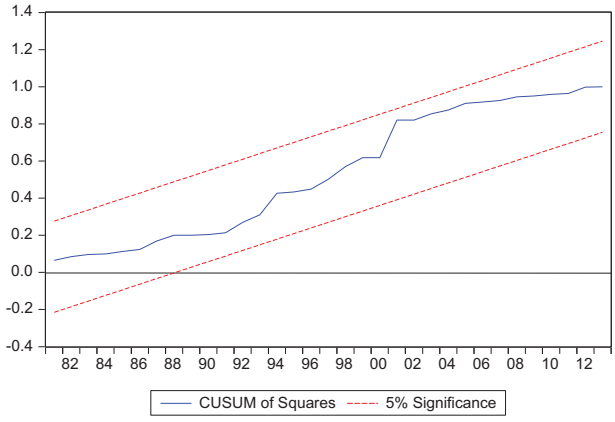

Table 7. Results of variance decomposition of LMR

Variance decomposition of LMR:

Period	S.E.	LMR	LFPI	LFR	LGDP	LHFCE
1	0.0054	100.0000	0.0000	0.0000	0.0000	0.0000
2	0.0120	98.2546	0.8676	0.1073	0.1794	0.5911
3	0.0195	96.6767	2.5612	0.0443	0.3374	0.3804
4	0.0272	95.6362	3.6116	0.1220	0.4039	0.2262
5	0.0345	94.8638	4.1769	0.2818	0.5282	0.1494
6	0.0412	93.9582	4.5950	0.5607	0.7809	0.1052
7	0.0473	92.9511	4.9727	0.9320	1.0571	0.0870
8	0.0529	91.9030	5.3384	1.3472	1.3258	0.0855
9	0.0581	90.8298	5.7486	1.7757	1.5490	0.0969
10	0.0631	89.7691	6.2241	2.1924	1.6963	0.1182

Table 8. Results of variance decomposition of LFPI

Variance decomposition of LFPI:

Period	S.E.	LMR	LFPI	LFR	LGDP	LHFCE
1	0.0785	21.8584	78.1416	0.0000	0.0000	0.0000
2	0.1022	14.1067	71.7527	8.1577	5.4074	0.5756
3	0.1183	15.0155	69.1801	6.7838	7.5888	1.4318
4	0.1375	15.2026	64.5553	6.9449	12.2355	1.0616
5	0.1546	16.6091	61.9796	7.6758	12.8606	0.8749
6	0.1700	18.4074	59.2603	8.0087	13.5559	0.7677
7	0.1854	20.0407	57.0345	8.2795	13.9905	0.6548
8	0.2001	21.1996	55.6676	8.5878	13.9788	0.5662
9	0.2137	21.8772	55.0291	8.7939	13.7997	0.5001
10	0.2265	22.0450	55.0258	8.9480	13.5353	0.4460

due to shocks in fertility rate. Meaning that food production index affects mortality rate more than fertility rate, GDP, and household final consumption expenditure in the long-run in Ghana. In other words, ending hunger and ensuring access to safe and nutritious food by children under-5, infants, and vulnerable will help reduce mortality rate in the long run.

Table 9. Results of variance decomposition of LFR

Variance decomposition of LFR:

Period	S.E.	LMR	LFPI	LFR	LGDP	LHFCE
1	0.0012	0.8411	26.7171	72.4418	0.0000	0.0000
2	0.0021	0.8485	36.7993	60.7015	1.4998	0.1510
3	0.0034	2.9529	39.8969	54.2308	0.8650	2.0544
4	0.0049	5.7429	44.2875	45.7131	1.3504	2.9060
5	0.0067	10.2887	46.5243	37.9103	1.7753	3.5015
6	0.0089	15.5397	47.5759	30.8720	2.3246	3.6879
7	0.0115	20.9925	47.3839	25.1585	2.7736	3.6916
8	0.0143	26.0718	46.5006	20.7434	3.0962	3.5880
9	0.0175	30.5320	45.2974	17.4443	3.2689	3.4573
10	0.0208	34.2993	44.0300	15.0153	3.3262	3.3292

Table 10. Results of variance decomposition of LGDP

Variance decomposition of LGDP:

Period	S.E.	LMR	LFPI	LFR	LGDP	LHFCE
1	0.0435	0.1989	5.6039	0.0360	94.1612	0.0000
2	0.0741	0.6890	5.2373	1.0623	93.0018	0.0096
3	0.0957	1.2433	5.0855	1.0226	92.0631	0.5855
4	0.1145	1.5982	5.0802	1.0896	91.4695	0.7625
5	0.1307	1.7132	5.2248	1.4102	90.8718	0.7800
6	0.1452	1.6566	5.2338	1.7608	90.5766	0.7722
7	0.1589	1.5159	5.2346	2.1092	90.4067	0.7337
8	0.1717	1.3745	5.3163	2.4628	90.1606	0.6859
9	0.1836	1.2673	5.4851	2.7863	89.8194	0.6419
10	0.1947	1.2086	5.7578	3.0707	89.3626	0.6003

Table 11. Results of variance decomposition of LHFCE

Variance decomposition of LHFCE:

Period	S.E.	LMR	LFPI	LFR	LGDP	LHFCE
1	0.1718	1.7435	2.1202	0.3432	10.0589	85.7342
2	0.2638	2.3100	1.9358	6.1334	10.1499	79.4709
3	0.3156	2.4014	2.7694	4.8026	12.5360	77.4907
4	0.3745	3.4772	2.5144	4.1302	16.4950	73.3832
5	0.4189	5.1366	2.1691	3.7195	17.3207	71.6541
6	0.4614	7.3705	1.9345	3.3454	17.7206	69.6290
7	0.5016	9.4461	1.7197	3.0472	17.9010	67.8860
8	0.5404	11.2311	1.5552	2.8507	18.0283	66.3348
9	0.5769	12.5804	1.4514	2.7088	18.2405	65.0190
10	0.6116	13.4883	1.3917	2.6135	18.5753	63.9313

From Table 8, almost 22% of future fluctuations in the food production index are due to shocks in mortality rate while 14% of future fluctuations in the food production index are due to shocks in GDP.

Meaning that mortality rate affects food production index more than GDP, fertility rates and household final consumption expenditure in the long-run in Ghana. Farming is mostly done by women in Ghana, therefore as child mortality increases high birthrate increases compensate the high mortality rate which leads to reduced productivity in farming leading to reduced food production index.

From Table 9, almost 44% of future fluctuations in fertility rate are due to shocks in the food production index while 34% of future fluctuations in fertility rate are due to shocks in mortality rate. Meaning that food production index affects fertility rate more than mortality rate, GDP, and household final consumption expenditure in the long-run in Ghana. Due to food demand in Ghana, poor agricultural practices like the intensive use of fertilizers and pesticides are used in agricultural production. From the results, as food production index in Ghana increases due to the intensive use of fertilizers and pesticides, the more fertility rate decreases. Simply put, increasing food production with unsustainable agricultural practices will affect future fertility rates.

From Table 10, almost 6% of future fluctuations in GDP are due to shocks in the food production index while 3% of future fluctuations in GDP are due to shocks in fertility rate. Meaning that food production index affects GDP more than fertility rate, mortality rate, and household final consumption expenditure in the long-run in Ghana.

Finally, results from Table 11 show that almost 19% of future fluctuations in household final consumption expenditure are due to shocks in GDP, while 13% of future fluctuations in household final consumption expenditure are due to shocks in mortality rate. Meaning that GDP affects household final consumption expenditure more than mortality rate, fertility rate, and the food production index in the long-run in Ghana.

4. Conclusion

In this study, the causal nexus between child mortality rate, fertility rate, GDP, household final consumption expenditure, and food production index in Ghana was investigated spanning from 1971 to 2013 using the ARDL method. The study tested for unit root, ARDL bounds test cointegration, ARDL long-run relationship, Granger causality test, and finally performed a Variance Decomposition Analysis using Cholesky technique. Results from the study are as follows:

There was evidence of long-run equilibrium relationship running from fertility rate, food production index, GDP, and household final consumption expenditure to mortality rate. There was evidence of a bidirectional causality running from household final consumption expenditure to fertility rate.

Evidence from the variance decomposition within a 10-period horizon shows that, almost 6% of future fluctuations in mortality rate are due to shocks in the food production index while 2% of future fluctuations in mortality rate are due to shocks in fertility rate. In other words, ending hunger and ensuring access to safe and nutritious food for children under-5, infants, and vulnerable will help reduce mortality rate in the long run.

Almost 22% of future fluctuations in the food production index are due to shocks in mortality rate while 14% of future fluctuations in the food production index are due to shocks in GDP. Farming is mostly done by women in Ghana; therefore, as child mortality increases, high birthrate increases to compensate the high mortality rate which leads to reduced productivity in farming, leading to a reduction in food production index.

Nearly 44% of future fluctuations in fertility rate are due to shocks in the food production index while 34% of future fluctuations in fertility rate are due to shocks in mortality rate. Due to food demand in Ghana, poor agricultural practices like the intensive use of fertilizers and pesticides are used in agricultural production. From the results, as food production index in Ghana increases due to the intensive use of fertilizers and pesticides, the more fertility rate decreases. Simply put, increasing food production with unsustainable agricultural practices will affect the future fertility rates.

Almost 6% of future fluctuations in GDP are due to shocks in the food production index while 3% of future fluctuations in GDP are due to shocks in fertility rate. Almost 19% of future fluctuations in household final consumption expenditure are due to shocks in GDP, while 13% of future fluctuations in household final consumption expenditure are due to shocks in mortality rate. Evidence from the study shows that the increasing levels of social determinants like Gross Domestic Product and Household final consumption expenditure will help reduce child mortality rates in Ghana.

The following policy recommendations are made based on the results of the study:

- Implementing policies ensure sustainable food production systems and implementing good agricultural practices will help end hunger and ensure access to safe and nutritious food for children and women that will reduce child mortality.
- Since the high mortality rate leads to high birth rates due to increased fertility rate, Government of Ghana should institute policies that ensure access to quality essential health care services, safe, effective, quality and affordable medicines that can help reduce preventable under-5 deaths.

Finally, instituting policies that empower women financially and the awareness of reducing under-5 deaths will help Ghana in achieving the 25 or less under-5 deaths per 1,000 live births before 2030.

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