The impact of food insecurity on health outcomes: Empirical evidence from sub-Saharan African countries

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Research Article

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Abstract

Background: Globally, food insecurity is a leading cause of morbidity and mortality through other diseases, which means food security and nutrition are crucial to improving people's health outcomes. Both food insecurity and the health outcomes are the policy and agenda of the 2030 Sustainable Development Goals (SDGs). However, there is a lack of macro-level empirical studies concerning the relationship between food insecurity and health outcomes in sub-Saharan African (SSA) countries, even though the region is highly affected by food insecurity and its related health problems. Therefore, this study aims to examine the impact of food insecurity on life expectancy and infant mortality in SSA countries.

Methods: The study uses secondary panel data collected from international institutions. It also mainly employs Driscoll-Kraay standard errors (DKSE), a generalised method of momentum (GMM), fixed effects (FE) and Granger causality approaches, along with others estimation techniques for robustness checks.

Results: The DKSE result of ***model 1A*** confirms that a one percent increment in people's prevalence for undernourishment reduces their life expectancy by 0.0034 percentage points. However, a one percentage increment in average dietary energy supply increases SSA countries' life expectancy by 0.0031 percentage points in ***model 1B***. The FE results show that a one percent increment in the prevalence of undernourishment leads to an enhancement of infant mortality by 0.0119 percentage points in ***model 1C***. However, the GMM result for ***model 1D*** confirms that a one percent increment in average dietary energy supply reduces infant mortality by 0.0004 percentage points.

Conclusions: Food insecurity harms the health status of SSA countries, but food security impacts in the reverse direction. In other words, prevalence of undernourishment adversely affects life expectancy and it increases infant mortality. Moreover, an improvement in average dietary energy supply can improve life expectancy and reduces infant mortality. The study recommends efficient utilisation of resources; improvements in investment in agricultural research, markets, infrastructures, macroeconomic policies and institutions; and developing sub-region strategies based on their agro-ecological zone, all of which are essential to overcome food insecurity and improve health outcomes.

Background

Food security is an essential element of people's health and well-being [1]. Further, the World Health Organization (WHO) argues that health is wealth and poor health is an integral part of poverty; governments should actively seek to preserve their people's lives and reduce the incidence of unnecessary mortality and avoidable illnesses [2]. However, lack of food is one of the factors which affects health outcomes. Concerning this, the Food Research and Action Center noted that the social determinants of health, such as poverty and food insecurity, are associated with some of the most severe and costly health problems in a nation [3].

According to the Food and Agricultural Organization (FAO), the International Fund for Agricultural Development (IFAD) and the World Food Programme (WFP), food insecurity is defined as "A situation that exists when people lack secure access to sufficient amounts of safe and nutritious food for normal growth and development and an active and healthy life" [4; p50]. It is generally believed that food security and nutrition are crucial to improving human health and development. Studies show that millions of people live in food insecurity, which is one of the main risks to human health. Around one in four people globally (1.9 billion people) were moderately or severely food insecure in 2017, and the greatest numbers were in SSA and South Asia. Around 9.2% of the world's population were severely food insecure in 2018. Food insecurity is highest in SSA countries, where nearly one-third are defined as severely insecure [5]. Similarly, 11% (820 million) of the world's population were undernourished in 2018, and SSA countries still share a substantial amount [5]. Even though globally the number of people affected by hunger has been decreasing since 1990, in recent years (especially since 2015) the number of people living in food insecurity has increased. It will be a huge challenge to achieve the SDGs of zero hunger by 2030 [6]. Even recently, the Global Report on Food Crises confirmed that 135 million people worldwide faced acute levels of hunger in 2019. Moreover, the report estimated that 183 million others experienced stressed food security and were at risk of falling into critical food insecurity levels, and the majority of them (around 73 million people) live in Africa [7].

An important consequence of food insecurity is that around 9 million people worldwide die every year due to hunger and hunger-related diseases. This is more than from Acquired Immunodeficiency Syndrome (AIDS), malaria and tuberculosis combined [6]. Similarly, about half of the world's deaths occur among children in SSA due to food insecurity [8].

With the above information, researchers and policymakers should focus on the issue of food insecurity and health status. The SDGs that were developed in 2015 intend to end hunger in 2030 as one of its primary targets. However, there is a growing number of people living with hunger and food insecurity, leading to millions of deaths. In addition, despite the evidence implicating food insecurity and poor health status, there is a lack of macro-level empirical studies concerning the impact of food insecurity on people's health status in SSA countries, which leads to a knowledge (literature) gap. Therefore, this study aims to examine the impact of food insecurity on life expectancy and infant mortality in SSA countries for the period ranging from 2001–2018 using panel mean regression approaches.

Theoretical And Conceptual Framework

The conceptual framework of food insecurity and health was developed by Weiser et al. [9], who postulate that food insecurity and health are interconnected in a vicious circle via nutritional, mental health and behavioural pathways (for more detail, see [9]). Since this study focuses on the impact of food insecurity on health outcomes, and not on the causes, it adapts the conceptual framework of [9] and constructed Fig. 1.

Source: Modified and constructed by the author using Weiser et al. (9) conceptual framework.

Several findings associate the negative impact of food insecurity on health outcomes. For instance, Stuff et al. [10] found that food insecurity is related to poor self-reported health status, obesity [11], abnormal blood lipids [12], a rise in diabetes [12, 13], increased gestational diabetes [14], increased perceived stress, depression and anxiety among women [15, 16], Human Immunodeficiency Virus (HIV) acquisition risk [17–19], childhood stunting [20], poor health [21], mental health and behavioural problem [16].

Methods

This section discusses the methodology of this study. Specifically, it provides data type, sources, model specification and basic panel data econometric tests along with their justifications. It further provides estimation techniques, procedures and justifications.

Data type, sources and model specification

Except for mean years of schooling (from the United Nations Development Programme[1]) and average dietary energy supply (from the FAO[2]), all the data were collected from the World Bank[3]. Notably, the data were collected from 31 SSA countries (Angola, Benin, Botswana, Burkina Faso, Cameroon, Cabo Verde, Chad, Congo Rep., Côte d'Ivoire, Ethiopia, Gabon, The Gambia, Ghana, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Sudan, Tanzania and Togo). Since SSA countries suffer from food insecurity and its related health problems, this study believes the sampled countries are appropriate. Further, this study's time scope (from 2001–2018) is also appropriate because it captures the Millennium Development Goals, SDGs and other economic conditions such as the rise of SSA countries' economies and the global financial crisis of the 2000s. Therefore, this study considers various global development programmes and events.

Besides social factors, the study includes economic factors determining people's health status. Moreover, it uses two proxies' indicators to measure both food insecurity and health status; hence, it specifies the general model as follows:

$$\overbrace{LNLEXP(LNINFMOR)}^{Targetvariables} = f(\overbrace{PRUND(AVDES)}^{Targetvariables}, GDPPC, GOVEXP, MNSCHOOL, URBAN)\,(1)$$

The study uses four models to analyze the impact of food insecurity on health outcomes.

$$LNLEXP_{it} = \alpha_0 + \alpha_1 PRUND_{it} + \alpha_2 GDPPC_{it} + \alpha_3 GOVEXP_{it} + \alpha_4 MNSCHOOL_{it} + \alpha_5 URBAN_{it} + {}_{it}\,(1A)$$

$$LNLEXP_{it} = \beta_0 + \beta_1 AVDES_{it} + \beta_2 GDPPC_{it} + \beta_3 GOVEXP_{it} + \beta_4 MNSCHOOL_{it} + \beta_5 URBAN_{it} + v_{it}\,(1B)$$

$$LNINFMOR_{it} = \theta_0 + \theta_1 PRUND_{it} + \theta_2 GDPPC_{it} + \theta_3 GOVEXP_{it} + \theta_4 MNSCHOOL_{it} + \theta_5 URBAN_{it} + \epsilon_{it}\,(1C)$$

$$LNINFMOR_{it} = \delta_0 + \delta_1 AVDES_{it} + \delta_2 GDPPC_{it} + \delta_3 GOVEXP_{it} + \delta_4 MNSCHOOL_{it} + \delta_5 URBAN_{it} + \mu_{it}\,(1D)$$

where LNLEXP and LNINFMOR refer to the natural logarithm of life expectancy at birth and infant mortality used as proxy variables for health outcomes. Similarly, PRUND and AVDES are the prevalence of undernourishment and average dietary energy supply adequacy – proxy variables for food insecurity. GDPPC is GDP per capita, GOVEXP refers to domestic general government health expenditure, MNSCHOOL is mean years of schooling and URBAN refers to urbanisation. Further, $_{it}, v_{it}, \epsilon_{it}, and \mu_{it}$ are the stochastic error terms at period *t*. The parameters $\alpha_{0,}\beta_0, \theta_0, \delta_0$ refer to intercept terms and $\alpha_1 - \alpha_5, \beta_1 - \beta_5, \theta_1 - \theta_5, and \delta_1 - \delta_5$ are the long-run estimation coefficients. Since health outcomes and food insecurity have two indicators used as proxy variables, this study estimates different alternative models and robustness checks of the main results.

Basic panel econometric tests and their justifications

Cross-sectional dependence (CD)

A growing body of the panel data literature concludes that panel data models are likely to exhibit substantial CD in the errors resulting from frequent shocks, unobserved components, spatial dependence and idiosyncratic pairwise dependence. Even though the impact of CD in estimation depends on several factors, relative to the static model, the effect of CD in dynamic panel estimators is more severe [22]. Moreover, Pesaran [23] notes that occurrences such as recessions and economic or financial crises potentially affect all countries, even though it might start from just one or two countries. These occurrences inevitably introduce some cross-sectional interdependencies across the cross-sectional unit, their regressors and the error terms. Hence, overlooking the CD in panel data leads to biased estimates and spurious results [22, 24]. Further, the CD test determines the type of panel unit root and cointegration tests that we should apply. Therefore, examining the CD is vital and is the first step in panel data econometrics.

In the literature, there are several tests for CD, such as the Breusch and Pagan [25] Lagrange multiplier (LM) test, Pesaran [26] scaled LM test, Pesaran [26] CD test and Baltagi et al. [27] bias-corrected scaled LM test (for more detail, see Tugcu and Tiwari [28]). Besides, Friedman [29] and Frees [30, 31] also other types of CD tests (for more detail, see De Hoyos and Sarafidis [22]). This study basically employs Frees [30] and Pesaran [26] among the existing CD tests. This is because, unlike the Breusch and Pangan [25] test, these tests do not require infinite T and fixed N, and are rather applicable for both a large N and T. Additionally, Free's CD test can overcome the irregular signs associated with correlation. However, it also employs Friedman [29] CD for mixed results of the above tests.

Unit root test

The panel unit root and panel cointegration tests are also the common steps following the CD test. Generally, there are two types of panel unit root test: (1) the first-generation panel unit root tests, such as Im et al. [32], Maddala and Wu [33], Choi [34], Levin et al. [35], Breitung [36] and Hadri [37], and (2) the second-generation panel unit root tests, such as [24, 38–47].

The first-generation panel unit root tests have been criticised because they assume cross-sectional independence [48–51]. This hypothesis is somewhat restrictive and unrealistic, as macroeconomic time series exhibit significant cross-sectional correlation among countries in a panel [50], and co-movements of economies are often observed in the majority of macroeconomic applications of unit root tests [49]. The cross-sectional correlation of errors in panel data applications in economics is likely to be the rule rather than the exception [51]. Moreover, applying first-generation unit root tests under CD models can generate substantial size distortions [48], resulting in the null hypothesis of nonstationary being quickly rejected [24, 52]. As a result, second-generation panel unit root tests have been proposed to take CD into account. Therefore, among the existing second-generation tests, this study employs Pesaran's [24] cross-sectionally augmented panel unit root test (CIPS) unit root test for models 1A–1C. The rationale for this is that, unlike other unit root tests that allow CD, such as Bai and Ng [38], Moon and Perron [45] and Phillips and Sul [42], Pesaran's [24] test is simple and clear. Besides, Pesaran [24] is robust when time-series' heteroscedasticity is observed in the unobserved common factor [53]. Even though theoretically Moon and Perron [45], Choi [54] and Pesaran [24] require large N and T, Pesaran [24] is uniquely robust in small sample sizes [55]. Therefore, this study employs the CIPS test to take into account CD, heteroskedasticity in the unobserved common factor and both large and small sample countries. However, since there is no CD in model 1D, this study employs the first-generation unit root tests called Levin, Lin, and Chu (LLC), Im, Pesaran, Shin (IPS) and Fisher augmented Dickey–Fuller (ADF) for model 1D.

Cointegration test

The most common panel cointegartion tests when there is CD are Westerlund [56], Westerlund and Edgerton [57], Westerlund and Edgerton [58], Groen and Kleibergen [59], Westerlund's [60] Durbin-Hausman test, Gengenbach et al. [61] and Banerjee and Carrion-i-Silvestre [62]. However, except for a few, most of them are not coded in Statistical Software (STATA) or Econometrics Views (EViews) and are affected by insufficient observations. The current study primarily uses Westerlund [56] and Banerjee and Carrion-i-Silvestre [62]

for models 1A–1C. However, to decide uncertain results, it also uses McCoskey and Kao [63] cointegration tests for model 1C. The rationale for using Westerlund's [56] cointegration test is that most panel cointegration has failed to reject the null hypothesis of no cointegration due to failure of common-factor restriction [64]. However, Westerlund [56] does not require any common factor restriction [65] and allows for a large degree of heterogeneity (e.g. individual-specific short-run dynamics, intercepts, linear trends and slope parameters) [50, 65, 66]. Besides, its command is coded and easily available in STATA. However, it suffers from insufficient observations, especially when the number of independent variables increases. The present study employs the Banerjee and Carrion-i-Silvestre [62] and McCoskey and Kao [63] cointegration tests to overcome this limitation. The three Engle-Granger-based cointegration tests applicable when there is no CD and which are widely used and available in EViews and STATA are Pedroni [67, 68], Kao [69] and Fisher-type [34]. Compared to the Fisher-type, both the Pedroni and Kao cointegration tests are more efficient and comprehensive. This study therefore uses them for model 1D.

Estimation techniques, procedures and justifications

This study mainly employs the Driscoll-Kraay [70] standard error (DKSE) (for models 1A and 1B), FE (for model 1C) and two-step GMM (for model 1D) estimation techniques to examine the impact of food insecurity on health outcomes. It also employs the Granger causality test. However, for robustness checks, it employs fully modified ordinary least square (FMOLS), dynamic OLS (DOLS), panel-corrected standard error (PCSE) and feasible generalised least squares (FGLS) methods (for models 1A and 1B), random effect (RE) techniques for model 1C and panel dynamic fixed effect (DFE) techniques for model 1D.

Even though several panel estimation techniques allow CD, most of them – such as cross-section augmented autoregressive distributed lag (CS-ARDL), cross-section augmented distributed lag (CS-DL), common correlated effects pooled (CCEP) and common correlated effects mean group (CCEMG) estimators – require a large number of observations over groups and time periods. Similarly, the continuously updated full modified (CUP-FM) and continuously updated bias-corrected (CUP-BC) estimators are not coded in both STATA and EViews. Others, like the PCSE, FGLS and seemingly unrelated regression (SUR), are feasible for T (the number of time series) > N (the number of cross-sectional units) [71, 72]. However, a DKSE estimate is feasible for N > T [71]. Therefore, depending on the CD, cointegration test, availability in STATA and EViews and comparing N against T, this study mainly employs the DKSE regression for models 1A and 1B. Due to the absence of cointegration, and to deal with heterogeneity and spatial dependence in the dynamic panel, this study employs FE for model 1C. However, due to the absence of CD, the existence of cointegration and N > T, and because all variables are I(1), this study uses GMM for model 1D.

The DKSE regression can be estimated in three different ways: FE with DKSE, RE with DKSE and pooled Ordinary Least Squares/Weighted Least Squares (pooled OLS/WLS) regression with DKSE. Hence, we have to choose the most efficient model using Hausman and Breusch-Pagan LM for RE tests. In other words, we have to select the most efficient model among FE, RE and Pooled OLS for models 1A and 1B; a more efficient model between FE and RE for model 1C; and the most efficient of the panel ARDL (Pooled Mean Group (PMG), Mean Group (MG), and DFE) models. Therefore, this study uses a FE model within the DKSE estimates for models 1A and 1B, and a FE model for model 1C (in the interest of space, these results are not reported here but are available from the author).

Finally, to check the robustness of the main result, this study employs FMOLS, DOLS, FGLS and PCSE estimation techniques for models 1A and 1B. Even though the Hausman test confirms that the FE is more efficient, the study employs the RE model for model 1C. This is because Firebaugh et al. [73] note that the RE and FE models are the best performers in panel data. Besides, unlike FE, RE assumes that the differences between individuals are random. This study also uses panel DFE for model 1D (selected based on Hausman test). Moreover, the robustness check is also conducted using an alternative model (i.e. dependent variable without natural log and Granger causality test).

Results

Basic panel econometric tests

Each of Tables 1–3 provide a basic econometric test which is a precondition for panel estimations. Specifically, it has basic information about the CD, unit root (stationary) behaviour of all the variables as well as cointegration (long-run relationship) among the variables in the models.

Table 1
Cross-sectional dependence tests

tests	***Model 1A***	***Model 1B***	***Model 1C***	***Model 1D***
Pesaran's test of CD	8.862***	5.971***	3.673***	0.148
Frees' test of cross sectional independence	10.067***	10.309***	8.010***	8.386***
Friedman's test of cross sectional independence	-	-	-	16.254
CD Cross-Sectional Dependence				
*** ⇒ significant at 1% level.				
Source: Computed by the author using STATA 15				

Table 2
Unit root tests

Pesaran [26] unit root test (*Models 1A–1C*)

Variables	CIPS (intercepts only)		Critical values		
	Levels	1st difference			
	Statistic	Statistic	10%	5%	1%
LNLEXP	-3.839***	-2.854***	-2.03	-2.11	-2.25
LNINFMOR	-1.884	-2.548***			
PRUDN	-1.528	-2.280***			
AVRDES	-2.110**	-2.518***			
GDPPC	-0.978	-2.800***			
GOVEXP	-1.550	-3.925***			
MNSCHOOL	-2.036*	-4.070***			
URBAN	-1.997	-2.976***			

Unit root test[E] (Model 1D)

LNINFMOR	Statistic	Values	Order of integration
	LLC	-7.69760***	All variables are I(1)
	IPS	-5.51904***	
	ADF	149.259***	
AVRDES	LLC	-2.37413***	
	IPS	-4.67357***	
	ADF	120.522***	
GDPPC	LLC	-14.8520***	
	IPS	-10.1380***	
	ADF	228.426***	
GOVEXP	LLC	-18.0049***	
	IPS	-16.3343***	
	ADF	335.915***	
MNSCHOOL	LLC	-11.8124***	
	IPS	-12.9479***	
	ADF	279.960***	
URBAN	LLC	-21.3499***	
	IPS	-15.3157***	
	ADF	209.195***	

ADF Augmented Dickey–Fuller, AVRDES Average Dietary Energy Supply, CIPS Cross-Sectionally Augmented Panel Unit Root Test, GDPPC Gross Domestic product (GDP) per capita, GOVEXP Domestic General Government Health Expenditure, I(1) Integration at First Difference, IPS Im, Pesaran, Shin, LLC Levin, Lin, and Chu, LNINFMOR Natural Logarithm of Infant Mortality Rate, LNLEXP Natural Logarithm of Life Expectancy at Birth, MNSCHOOL Mean Years of Schooling, PRUDN Prevalence of Undernourishment, URBAN Urbanisation.

***, **, * ⇒ significant at 1, 5, and 10% level, respectively.

Source: Computed by the author using STATA 15 and EViews 10[E]

Following unit root tests, Table 3 also reports a basic econometric test called the panel cointegration test, which describe the long-run relationship among the variables.

Table 3
Panel cointegration test

Models	**Values**	**Westerlund [56] test for only target variables**				**Banerjee and Carrion-i-Silvestre [62] – for all variables in the model**
		Gt	**Ga**	**Pt**	**Pa**	**Levels Statistic**
Model 1A	Z-value	-34.004***	-1.463*	-74.878***	-34.439***	-4.062***
	Bootstrap P-value	0.000***	0.000***	0.000***	0.000***	
Model 1B	Z-value	-34.708***	-4.303***	-52.636***	-37.899***	-4.212***
	Bootstrap P-value	0.000***	0.000***	0.000***	0.000***	
Model 1C	Z-value	6.958	7.497	3.508	4.582	-2.907***
	Bootstrap P-value	0.990	0.990	0.440	0.380	

Further cointegration tests (Model 1C)					
DOLS residuals	Included variables	Unit root test	Statistic		p-value
	between target variables	IPS	t-bar	-1.5321	0.9509
			t-tilde-bar	-1.1501	
			Z-t-tilde-bar	1.6541	
	All variables in the model	IPS	t-bar	-1.2116	0.9984
			t-tilde-bar	-0.9728	
			Z-t-tilde-bar	2.9494	

Pedroni [66] cointegrtaion test[E] (Model 1D)				
	Test		Statistics	Weighted Statistic
Within-dimension	Panel	v-Statistic	-0.238	0.903
		rho-Statistic	4.791	4.046
		PP-Statistic	1.140	-1.568*
		ADF-Statistic	-2.103**	-2.733***
Between-dimension	Group	rho-Statistic	6.215	
		PP-Statistic	-4.147***	
		ADF Statistic	-3.553***	

Kao [69] co-integration test[E] (Model 1D)	
Tests	t-Stat.
ADF	-2.637***

ADF Augmented Dickey–Fuller, IPS Im, Pesaran and Shin.

*, **, *** ⇒ significant at 10%, 5%, and 1% level, respectively.

Source: Computed by the author using STATA 15 and EViews 10[E]

Long-run estimation results

Table 4 provides regression results of all models employing appropriate estimation techniques such as DKSE, FE, two-step GMM and Granger causality.

Table 4
DKSE, FE, Two-step GMM, and Granger causality results…main result

Variables	DKSE		FE	GMM
	Dependent variable (LNLEXP)		Dependent variable (LNINFMOR)	
	Model 1A	Model 1B	Model 1C	Model 1D
PRUDN	-0.0034***	—	0.0119***	—
L_LNINFMOR	—	—	—	0.9698***
AVRDES	—	0.0031***	—	-0.0004***
GDPPC	-4.28e-06	-3.81e-06	0.000056***	1.97e-06
GOVEXP	0.0047	0.0018	-0.0103	-0.0026***
MNSCHOOL	0.0936***	0.0926***	-0.281***	-0.0034
URBAN	-0.0001	-0.0001	0.00061	0.00003
CONSTANT	3.7019***	3.2941***	4.904***	—
Dumitrescu and Hurlin [74] **Granger causality test**[E]				
Null hypothesis		W-Stat.(Zbar-Stat.)		
$\mathrm{PRUDN} \nrightarrow \mathrm{LNLEXP}$		17.532 (48.436)***		
$\mathrm{AVRDES} \nrightarrow \mathrm{LNLEXP}$		13.272(35.829)***		
$\mathrm{PRUDN} \nrightarrow \mathrm{LNINFMOR}$		5.007(11.368)***		
$\mathrm{AVRDES} \nrightarrow \mathrm{LNINFMOR}$		5.277(12.166)***		
AVRDES Average Dietary Energy Supply, DKSE Driscoll-Kraay Standard Errors, FE Fixed Effect, GDPPC Gross Domestic product (GDP) per capita, GMM Generalised Method of Momentum, GOVEXP Domestic General Government Health Expenditure, L_LNINFMOR Lag of Natural Logarithm of Infant Mortality Rate, LNINFMOR Natural Logarithm of Infant Mortality Rate, LNLEXP Natural Logarithm of Life Expectancy at Birth, MNSCHOOL Mean Years of Schooling, PRUDN Prevalence of Undernourishment, URBAN Urbanisation				
*** ⇒ significant at 1% level.				

Source: Computed by the author using STATA 15 and EViews 10[E]

Robustness checks

Since the above result is not enough for concrete conclusions and policy recommendations, Tables 5 and 6 provide estimation results to check the robustness of Table 4 results. Except for differences in the dependent variables or estimation techniques, the robustness results are similar to Table 4 concerning the relationship between target variables.

Table 5
DKSE, FE, Two-step GMM, and Granger causality results

Variables	DKSE		FE	GMM
	Dependent variable (LEXP)		Dependent variable (INFMOR)	
	Model 1A	Model 1B	Model 1C	Model 1D
PRUDN	-0.1924***	—	0.9785***	—
L_INFMOR	—	—	—	0.9576***
AVRDES	—	0.1762***	—	-0.0119
Dumitrescu and Hurlin [74] **Granger causality test**[E]				
Null hypothesis		W-Stat.(Zbar-Stat.)		
$\mathrm{PRUDN} \nrightarrow \mathrm{LEXP}$		18.330(50.799)***		
$\mathrm{AVRDES} \nrightarrow \mathrm{LEXP}$		14.289(38.838)***		
$\mathrm{PRUDN} \nrightarrow \mathrm{INFMOR}$		5.491(12.801)***		
$\mathrm{AVRDES} \nrightarrow \mathrm{INFMOR}$		5.755(13.580)***		
AVRDES Average Dietary Energy Supply, DKSE Driscoll-Kraay Standard Errors, FE Fixed Effect, GMM Generalised Method of Momentum, INFMOR Infant Mortality Rate, L_INFMOR Lag of Infant Mortality Rate, LEXP Life Expectancy at Birth, PRUDN Prevalence of Undernourishment.				
*** ⇒ significant at 1% level.				

Source: Computed by the author using STATA 15 and EViews 10[E]

Table 6
FMOLS, DOLS, PCSE, FGLS, RE, and DFE results

Variables	FMOLS[E]		DOLS[E]		PCSE		FGLS	
	Dependent variable (LNLEXP)							
	Model 1A	Model 1B	Model 1A	Model 1B	Model 1A	Model 1B	Model 1A	Model 1B
PRUDN	-0.0033***	—	-0.0034 ***	—	-0.0024***	—	-0.0023***	—
AVRDES	—	0.0030***	—	0.0031***	—	0.0013***	—	0.0013***
Dependent variable (LNINFMOR)								
			RE for Model 1C		DFE for Model 1D			
PRUDN			0.01204***		—			
AVRDES			—		-0.0177***			
ECM			—		-0.0352***			
AVRDES Average Dietary Energy Supply, DFE Dynamic Fixed Effect, DOLS Dynamic Ordinary Least Square, ECM Error Correction Model, FGLS Feasible Generalised Least Squares, FMOLS Fully Modified Ordinary Least Square, LNINFMOR Natural Logarithm of Infant Mortality Rate, LNLEXP Natural Logarithm of Life Expectancy at Birth, PCSE Panel-Corrected Standard Error, PRUDN Prevalence of Undernourishment, RE Random Effect,								
*** ⇒ significant at 1% level.								

Source: Computed by the author using STATA 15 and EViews 10[E]

Discussion

Cross-sectional dependence test

Except for model 1D, the results strongly reject the null hypothesis of cross-sectional independence in all models. However, for model 1D, the study found mixed results (i.e. Pesaran [26] fails to reject the null hypothesis of no CD while Frees [30] strongly rejects it). Thus, in order to decide, this study employs the Friedman [29] CD test. The result fails to reject the null hypothesis of cross-sectional independence, implying that two out of three tests fail to reject the null hypothesis of cross-sectional independence in model 1D. Therefore, unlike others, there is no CD in model 1D (see Table 1).

Unit root tests

The result shows that all variables are highly (at 1% level) significant at the first difference (I(1)) in all models, which implies all variables are stationary at I(1). In other words, the result fails to reject the null hypothesis of unit root (non-stationary) for all variables at a 1% level of significance at the first difference. Since all the variables are highly statistically significant at the first difference, we notice that all measures are I(1). Thus, we might expect a long-run connection between these variables collectively (see Table 2).

Cointegration tests

The results in Table 3 show that both the Westerlund [56] and Banerjee and Carrion-i-Silvestre [62] cointegration tests strongly reject the null hypothesis of no-cointegration in models 1A and 1B. However, model 1C provides a mixed result, i.e. the Banerjee and Carrion-i-Silvestre [62] test rejects the null hypothesis of no cointegartion, yet the reverse is true for the Westerlund [56] test. Therefore, this study conducted further cointegration tests for model 1C. Even though Westerlund and Edgerton [57] suffer from insufficient observation, it is based on the McCoskey and Kao [63] LM test [75]. Thus, we can use a residual-based cointegration test in the heterogeneous panel framework proposed by McCoskey and Kao [63]. However, an efficient estimation technique of cointegrated variables is required, and hence the FMOLS and DOLS estimators are recommended. The residuals derived from the FMOLS and DOLS will be tested for stationarity with the null hypothesis of no cointegration amongst the regressors. Since the McCoskey and Kao [63] test involves averaging the individual LM statistics across the cross-sections, for testing the residuals FMOLS and DOLS stationarity, McCoskey and Kao [63] test is in the spirit of IPS (Im et al. [32]) [76].

Though FMOLS and DOLS are recommended for the residuals cointegration test, DOLS is better than FMOLS (for more detail, see Kao and Chiang [77]); therefore, this study uses a residual test derived from DOLS. The result fails to reject the null hypothesis of no cointegartion. Two (Banerjee and Carrion-i-Silvestre [62] and McCoskey and Kao [63]) out of three tests fail to reject the null hypothesis of no cointegartion; hence, we can conclude that there is no long-run relationship among the variables in model 1C.

Unlike other models, since there is CD in model 1D, this study employs the Pedroni [68] and Kao [69] cointegration tests for model 1D. The result strongly rejects the null hypothesis of no cointegartion, implying – similar to models 1A and 1B – that a long-run relationship among the variables in model 1D exists (see Table 3).

Long-run estimation results

Table 4 presents the estimated results, however die to limitations of space, this section discusses only the results of target variables. The DKSE result of model 1A confirms that the rise in the prevalence of undernourishment significantly reduces life expectancy of SSA countries. In other words, a one percent increment in the prevalence for undernourishment reduces life expectancy by 0.0034 percentage points. However, the FE results show that an increment in the prevalence of undernourishment has a positive and significant impact on infant mortality in model 1C. The DKSE estimations result in model 1B reveals that a one percentage increment in average dietary energy supply increases SSA countries' life expectancy by 0.0031 percentage points. However, the GMM result for model 1D confirms that a one percent increment in average dietary energy supply reduces infant mortality by 0.0004 percentage points. Moreover, this study conducted a panel Granger causality test to confirm whether or not food insecurity has a potential causality to health outcomes. The result demonstrates that the null hypothesis of change in both prevalence of undernourishment and average dietary energy supply does not homogeneously cause health outcomes is rejected at 1% level of significance, implying a change in food insecurity does Granger-cause health outcomes of SSA countries (see Table 4).

Based on the above results, we can conclude that food insecurity harms SSA nations' health outcomes. This is because prevalence of undernourishment leads to increased infant mortality by reducing the vulnerability, severity and duration of infectious diseases such as diarrhoea, pneumonia, malaria and measles. Similarly, prevalence of undernourishment can reduce life expectancy by increasing the

vulnerability, severity, and duration of infectious diseases. However, food security improves health outcomes – the rise in average dietary energy supply reduces infant mortality and it increases the life expectancy of individuals.

The author believes that the above findings and conclusion may not be enough for policy recommendations unless robustness checks are undertaken. Hence, the study estimated all models without the natural logarithm of the dependent variables (see Table 5, though in the interest of space, only results of target variables are reported). The model 1A result reveals that similar to the above results, prevalence of undernourishment significantly reduces individuals' life expectancy in SSA countries. That means a one percent increment in prevalence of undernourishment reduces the life expectancy by 0.1924 years. Moreover, in model 1B, improvement in average dietary energy supply positively and significantly affects life expectancy. In model 1C, an increment in prevalence of undernourishment has a positive and significant effect on the infant mortality rate of SSA countries. The FE result implies that a one percent increment in prevalence of undernourishment increases the infant mortality rate by 0.9785. The GMM result in model 1D indicates that improvement in average dietary energy supply significantly reduces infant mortality. Further, the Granger causality result confirms that the null hypothesis of change in prevalence of undernourishment and average dietary energy supply does not homogeneously cause health outcomes is rejected at 1% level of significance, implying a change in food insecurity does Granger-cause health outcomes of SSA countries (see Table 5).

The study also conducted further robustness checks using the same dependent variables (as Table 4) but different estimation techniques. The results confirm that prevalence of undernourishment has a negative and significant effect on life expectancy, but improvement in average dietary energy supply significantly increases life expectancy in SSA countries. However, prevalence of undernourishment has a positive and significant effect on infant mortality, though improvement in average dietary energy supply significantly reduces (see Table 6).

Conclusions

Millions of people are dying every year due to hunger and hunger-related diseases worldwide, especially in SSA countries. Currently, the link between food insecurity and health status is on researchers' and policymakers' agendas. However, macro-level findings in this area for most concerned countries have been given only limited attention. Therefore, this study examined the impact of food insecurity on life expectancy and infant mortality rate. The study mainly employs DKSE, FE, two-step GMM and Granger causality approaches, along with other estimation techniques for robustness checks for the years between 2001 and 2018. The result confirms that food insecurity harms SSA nations' health outcomes, while food security improves the health status. That means that a rise in undernourishment increases the infant mortality rate and reduces life expectancy. However, an increment in average dietary energy supply reduces infant mortality and increases life expectancy. Therefore, SSA countries need to guarantee their food accessibility both in quality and quantity, which improves health status. Both development experts and political leaders agree that Africa has the potential for agricultural outputs, can feed the continent and improve socio-economic growth. Besides, more than half of the world's unused arable land is found in Africa. Therefore, effective utilisation of natural resources is essential to achieve food security. Further, improvement in investment in agricultural research; improvement in markets, infrastructures, and institutions; good macroeconomic policies and political stability; and developing sub-region strategies based on their agro-ecological zone is crucial to overcome food insecurity and improve health status.

Abbreviations

ADF
Augmented Dickey–Fuller
AIDS
Acquired Immunodeficiency Syndrome
AVRDES
Average Dietary Energy Supply
CCEMG
Common Correlated Effects Mean Group
CCEP
Common Correlated Effects Pooled
CD

Cross-Sectional Dependence
CIPS
Cross-Sectionally Augmented Panel Unit Root Test
CS-ARDL
Cross-Section Augmented Autoregressive Distributed Lag
CS-DL
Cross-Section Augmented Distributed Lag
CUP-BC
Continuously Updated Bias-Corrected
CUP-FM
Continuously Updated Full Modified
DFE
Dynamic Fixed Effect
DKSE
Driscoll-Kraay Standard Errors
DOLS
Dynamic Ordinary Least Square
ECM
Error Correction Model
EViews
Econometrics Views
FAO
Food and Agricultural Organization
FE
Fixed Effect
FGLS
Feasible Generalised Least Squares
FMOLS
Fully Modified Ordinary Least Square
GDPPC
Gross Domestic product (GDP) per capita
GMM
Generalised Method of Momentum
GOVEXP
Domestic General Government Health Expenditure
HIV
Human Immunodeficiency Virus
I(1)
Integration at First Difference. IFAD:International Fund for Agricultural Development
INFMOR
Infant Mortality Rate
IPS
Im, Pesaran, Shin
L_INFMOR
Lag of Infant Mortality Rate
L_LNINFMOR
Lag of Natural Logarithm of Infant Mortality Rate
LEXP
Life Expectancy at Birth
LLC
Levin, Lin, and Chu

LM
Lagrange Multiplier
LNINFMOR
Natural Logarithm of Infant Mortality Rate
LNLEXP
Natural Logarithm of Life Expectancy at Birth
MG
Mean Group
MNSCHOOL
Mean Years of Schooling
OLS
Ordinary Least Squares
PCSE
Panel-Corrected Standard Error
PMG
Pooled Mean Group
PRUND
Prevalence of Undernourishment
RE
Random Effect
SDGs
Sustainable Development Goals
SSA
Sub-Saharan African
STATA
Statistical Software
SUR
Seemingly Unrelated Regression
URBAN
Urbanisation
WFP
World Food Programme, WHO:World Health Organization
WLS
Weighted Least Squares

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The author declares that there are no competing interests.

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Author contributions

SDB was collected, analysed and interpreted the data, and wrote and approved the paper for submission.

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Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Notes:

Data sources:

1. http://hdr.undp.org/en/data
2. https://knoema.com/FAOFSD2020/fao-food-security-data?location=1000180-sub-saharan-africa
3. https://databank.worldbank.org/source/world-development-indicators#

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Figures

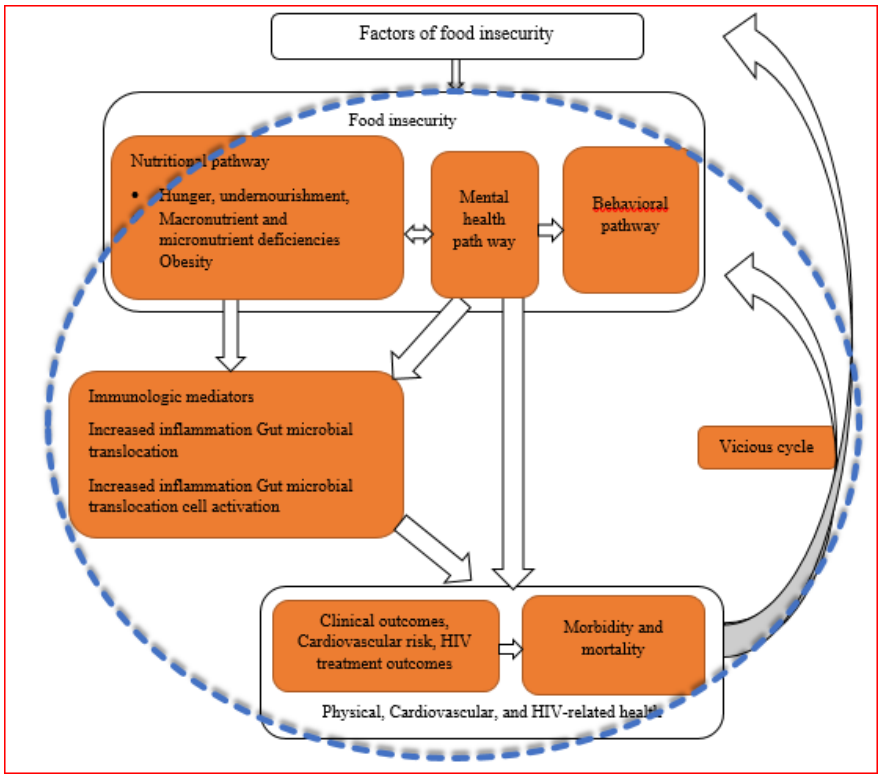

Figure 1

A conceptual framework of food insecurity and health

Source: Modified and constructed by the author using Weiser et al. (9) conceptual framework.